ESSAYS ON STRUCTURED FINANCIAL PRODUCTS

A thesis presented to the
Faculty of Management, Economics and Social Sciences
at the University of Fribourg (Switzerland)

by

Vladimir Anić
from Schmitten FR

in fulfillment of the requirements for the degree of
Doctor of Economics and Social Sciences

Accepted by the Faculty of Management, Economics and
Social Sciences on September 21, 2020 at the proposal of
Prof. Martin Wallmeier (first supervisor) and
Prof. Michael Burkert (second supervisor)

Fribourg (Switzerland), 2020

To my wife Jelena and my daughter Maja

PREFACE

"All great literature is one of two stories; a man goes on a journey or a stranger comes to town."

Leo Tolstoy

This literature is both of the two stories. I am not sure whether you will find it great. I hope you will though.

I would like to express my most sincere gratitude to my first supervisor Prof. Dr. Martin Wallmeier. His wisdom, competence, supportive attitude and sympathy have been invaluable for the completion of this thesis. I could not imagine a better supervisor for any student!

I also thank Prof. Dr. Michael Burkert (my second supervisor), Prof. Dr. Berno Büchel and Prof. Dr. Holger Herz for very helpful comments and constructive feedback on my work, my colleagues from the Department of Management and the Department of Economics of the University of Fribourg, in particular my office mates Christoph Iseli and Patrick Chardonnens, for the very pleasant cooperation and friendly atmosphere, my parents for their financial support, encouragement and warmth, and my wife Jelena and daughter Maja for everything ♡.

CONTENTS

LIST OF FIGURES

LIST OF TABLES

LIST OF ABBREVIATIONS

CLC	Constant leverage certificate
CPP	Capital protection product
DAX	German stock index
DJIA	Dow Jones Industrial Average
ELC	Endless leverage certificate
ETF	Exchange-traded fund
Eusipa	European Structured Investment Products Association
GARCH	Generalized autoregressive conditional heteroscedasticity
LETF	Leveraged exchange-traded fund
Libor	London Interbank Offered Rate
MLA	Myopic loss aversion
PF	Presentation format
RC	Reverse convertible
S&P	Standard & Poor's
VaR	Value-at-risk

LIST OF SYMBOLS

A_t	Risk-free investment at time t
A_i^p	Attractiveness of product p from the perspective of subject i
$C_t(\cdot)$	Function of the call price at time t
CLC_t	Price of the constant leverage certificate at time t
CPP_t	Price of the capital protection product at time t
D_t	Dividend payment at time t
$D_{i,Exp2}$	Dummy variable that takes on the value 1 if subject i participates in experiment 2
$D_{i,LF}$	Dummy variable that takes on the value 1 if subject i is in the low-frequency group
$D_{i,PF1}$	Dummy variable that takes on the value 1 if subject i is exposed to presentation format 1
$D_{i,PF2}$	Dummy variable that takes on the value 1 if subject i is exposed to presentation format 2
$D_{i,PF3}$	Dummy variable that takes on the value 1 if subject i is exposed to presentation format 3
f^I	Index fee
f^{SP}, f_t^{SP}	Financing spread (at time t)
f^{SR}, f_t^{SR}	Short sale fee (at time t)
H	Set of subjects in the high-frequency group
K	Minimum payoff
L	Set of subjects in the low-frequency group
m	Number of treatments
M	Maximum payoff
MI	Model intercept

n	Length of the investment period in days; sample size; number of shares
$P_t(\cdot)$	Function of the put price at time t
p_i, $p_{i,T}$	Probability of outcome i (with a given investment period T)
r, r_t	Risk-free return/interest rate (at time t)
$r^E_{t,\Delta t}$	Effective return in the period from t to Δt
$r^{E-F}_{t,\Delta t}$	Return deviation due to issuer fees in the period from t to Δt
$r^{E-N}_{t,\Delta t}$	Total return deviation in the period from t to Δt
$r^F_{t,\Delta t}$	Fair return in the period from t to Δt
$r^{F-T}_{t,\Delta t}$	Return deviation due to interest in the period from t to Δt
$r^N_{t,\Delta t}$	Leveraged cumulative return of the underlying in the period from t to Δt
$r^S_{t,\Delta t}$	Return of the stock/underlying asset in the period from t to Δt
$r^T_{t,\Delta t}$	Target return in the period from t to Δt
$r^{T-N}_{t,\Delta t}$	Return deviation due to compounding in the period from t to Δt
RC_t, $RC_{i,t}$	Price of the reverse convertible at time t (in outcome i)
$RC_{j,\tau,T}$	Wealth at time t in simulation path j after T reinvestments in reverse convertibles with term τ
s	Slope within the minimum and maximum payoff
S_t	Price of the stock/underlying asset at time t
T	Length of the investment period
$V(\cdot)$	Cumulative prospect theory utility function
$v(\cdot)$	Cumulative prospect theory value function
W_t	Standard Brownian motion at time t
W^p_i, $W^{p,s,f}_i$	(Average) investment weight of subject i and for product p (and for setting s and presentation format f)
$w(\cdot)$	Probability weighting function
$w^{p,s,f}_{i,t}$	Short-term investment weight of subject i, in period t, for product p, setting s and presentation format f
X_1, X_2	Strike prices of options
x_i	Outcome i
$x^S_{i,T}$	Outcome i of the stock index for a given investment period T

$x^{RC}_{i,\tau,T}$	Outcome i of the reverse convertible with term τ for a given investment period T
Z_i	Vector of control variables
α	GARCH parameter; cumulative prospect theory parameter
β	GARCH parameter; cumulative prospect theory parameter
β_0, β_1, β_2, ...	Regression coefficients
γ	Regression coefficient; cumulative prospect theory parameter
Δ	Effect size
$\Delta W^{p,s,f}$	Delta investment weight for product p, setting s and presentation format f
ΔZ	Scaling parameter
δ	Cumulative prospect theory parameter
ϵ, ϵ_t, ϵ_i^p, $\epsilon_i^{p,s,f}$	Error term (at time t, of subject i, for product p, setting s and presentation format f)
λ	Leverage factor; cumulative prospect theory parameter
μ	Price drift or mean return of the stock/underlying asset
μ_0	Mean of the dependent variable in the control group
μ_i	Mean of the dependent variable in the subject group with treatment i
π_i	Decision weight for outcome i
$\Phi(\cdot)$	Cumulative standard normal distribution function
σ, σ_t	Volatility of the stock (index)/underlying asset (at time t)
τ	One minus the tax rate; term of an option or a structured product
ω	GARCH parameter

Chapter 1
INTRODUCTION

In the past decades, the global financial system has undergone a radical evolution and financial innovation has become a defining characteristic of the industry. One of the major innovations that has gained importance as a complement to traditional investment instruments is an asset class broadly known as structured financial products. These products were launched in the early nineties and have become an important part of the asset universe today with a global market value estimated at USD 7 trillion. It is thus larger than, e.g., the market for exchange-traded funds (USD 5.3 trillion) or hedge funds (USD 2.9 trillion) (Faraj and Khaled, 2019).

1.1 What are Structured Products?

A common definition of structured products is that they are a combination of at least two financial assets, where at least one of them is a derivative. But meanwhile the variety of the market for these products has expanded so much that this definition is no longer considered appropriate. One of the reasons is that there exist many products that can be replicated without the use of derivatives. Accordingly, Blümke (2009, p. 7) has given the following alternative definition: "Structured products are financial assets, which consist of various elemental components, combined to generate a specific risk-return profile adapted to an investor's needs." However, there exist many products that cannot be replicated at all with standard financial instruments traded at exchanges. For this reason, an even more general definition is given in Rieger (2016, p. 170), stating that a structured product is a commitment of an issuer to make one or multiple payments at (a) predefined date(s), depending on the development of one or multiple underlying assets. This definition, however, might also capture financial products that are typically not considered as structured products. It is thus difficult to give a precise definition.

Structured products are issued and offered by banks and financial institutions. Issuers typically act as market makers by themselves such that the products can also be bought or sold on the secondary market. They are in most countries classified as unsecured debt and thus subject to counterparty risk (Rieger, 2016, p. 171). The main advantage over classic investment vehicles such as stocks, bonds and funds is that they come along with a huge variety of risk-return profiles, which allows them to meet individual market expectations and risk preferences of investors. For instance, an investor might expect an upward trending market but might be unwilling to put his/her capital at risk. This combination initially appears to be contradictory but can be met with so-called capital protection products, a combination of a bond and a call option on, e.g., an equity index. If the market has a favorable development, the holder of the product will receive the proceeds of the bond and the option. Otherwise, the option expires worthless, but the investor will still get back (a large fraction of) his capital since the redemption of the bond is independent of the equity index. These products work particularly well when the interest level is high.

In addition to capital protection products, several other product classes exist, with which other specific needs of investors can be addressed. The European Structured Investment Products Association (Eusipa) groups structured products into four investment product classes (capital protection products, yield enhancement products, participation products and credit linked notes) and three leverage product classes (leverage products without knock-out, leverage products with knock-out and constant leverage products) (Eusipa, 2019a).

1.2 What Is This Thesis About?

These increasingly complex products are often associated with a lack of transparency, which makes it difficult for investors to correctly assess the risk involved. For instance, after the collapse of Lehman Brothers during the financial crisis of 2007–2009, it became evident that many buyers of defaulted products were unaware of the counterparty risk associated with structured product investments. Since this event, the reputation of structured products is tarnished. (Blümke, 2009, p. 4–5).

But can a car be held responsible for an accident? Can a weapon be blamed for murder? No, but eventually it is the fault of the driver, the constructor, the government, the operator and/or the owner. With structured products, the situation is similar. Buyers are required to conduct due diligence. Financial institutions are obliged to disclose risks and advise clients in the clients' best interest. Regulators must supervise financial institutions and issue guidelines regarding the information to be provided to potential buyers. Finally, researchers must make meaningful discoveries, contribute knowledge, and increase the transparency and general understanding of these products.

The latter is also the objective of the present thesis. It includes three independent research projects in the context of structured financial products. The first project in Chapter 2 deals with constant leverage certificates, a relatively new and highly risky product type, which has not been addressed in the scientific literature so far. This is alarming, as these products have an insidious and treacherous onset: At first sight, they seem to be relatively easy to comprehend, but the mid- and long-term implications of the product design on the overall return are likely to be surprising for most inexperienced investors. This thesis closes the gap in the literature on constant leverage certificates by providing a profound analysis of the products' risk and return.

The other two projects are both included in Chapter 3 due to their thematic proximity. They share a common theoretical introduction about financial decision making, where some of the most important descriptive theories and cognitive biases are presented, and about experimental research, where a basic understanding of the methodology and the specifics of experiments in finance is developed.

The second project in Section 3.3, a joint work with Martin Wallmeier, was recently published in the Journal of Behavioral Finance (see Anic and Wallmeier, 2020). It examines the perceived attractiveness of structured products and how it is influenced by the way these products are presented. E.g., a capital protection product probably appears to be relatively attractive based on the description above. If the presentation of the product would be complemented by a return probability distribution, investors would realize that gaining a return greater than the protected level is actually low and consequently perceive the product as less attractive.

The third project in Section 3.4 is about a well known behavioral phenomenon named myopic loss aversion. It occurs when investors monitor their investments frequently, a natural process in the information age, and, as a result, experience a high loss frequency. In combination with their tendency to overweight losses over gains, investors invest smaller amounts in risky assets. This causal relationship between the evaluation frequency and the willingness to take risks is confirmed in many experimental studies. However, I assert that this relationship is not as reliable as prior literature suggests, especially in the context of structured product investments.

My argument is grounded on an elaborate theoretical study, where investment decisions are predicted by means of a well-established descriptive theory for human decision making known as cumulative prospect theory, and on a large-scale experimental study.

My thesis complies with its objective to increase the transparency in the market for structured financial products in many respects. First, it provides analyses that help potential investors to better understand the products' risk and return characteristics, to align them with their own risk and return preferences and market expectations, and to raise their awareness of how the information presented by issuers affects their decisions. Second, issuers can use the studies' insights to (re)design their sales brochures and other documents in order to better align them with the clients' needs. Finally, the results obtained through the three studies are also important for regulators to hinder issuers from exploiting behavioral biases by improving and increasing the minimum information requirements in information documents.

Chapter 2

CONSTANT LEVERAGE CERTIFICATES – AN ANALYSIS OF RISK AND RETURN

2.1 Introduction

Constant leverage certificates (CLCs), also called factor certificates, rolling turbos or factor turbos, are a relatively new type of investment product and popular mainly in Germany and Switzerland. The worldwide first issuer of CLCs was, to the best of my knowledge, Goldman Sachs. The bank introduced these certificates in 2004 in the German market. UBS was the first issuer to offer the product on the Swiss market. The bank launched a few CLCs in 2009 with commodities as underlying asset and leverage factors of -2 and 2 but refrained from issuing further products in subsequent years. Commerzbank followed in 2010 with various new products. They remained the only issuer of new CLCs in Switzerland until the beginning of 2014 when Vontobel entered the market. Since then, the market is dominated by these two issuers. Today, there are more than 2 000 CLCs listed at SIX Swiss Exchange and more than 4 500 CLCs from 13 different issuers listed at Euwax, Europe's largest platform for exchange trading in securitized derivatives. The outstanding volume in Germany varied between EUR 200 and 500 millions in the past years (Eusipa, 2019b).

CLCs enable investors to achieve overproportional gains with constant leverage on a daily basis. For instance, a 1% daily increase of the price of the underlying asset results in a 1% times the leverage factor increase of the CLC. Due to the constant leverage, the product is relatively easy to understand for potential investors and appears to be an attractive investment opportunity when comparing it to other leveraged products. Given this product design, it seems

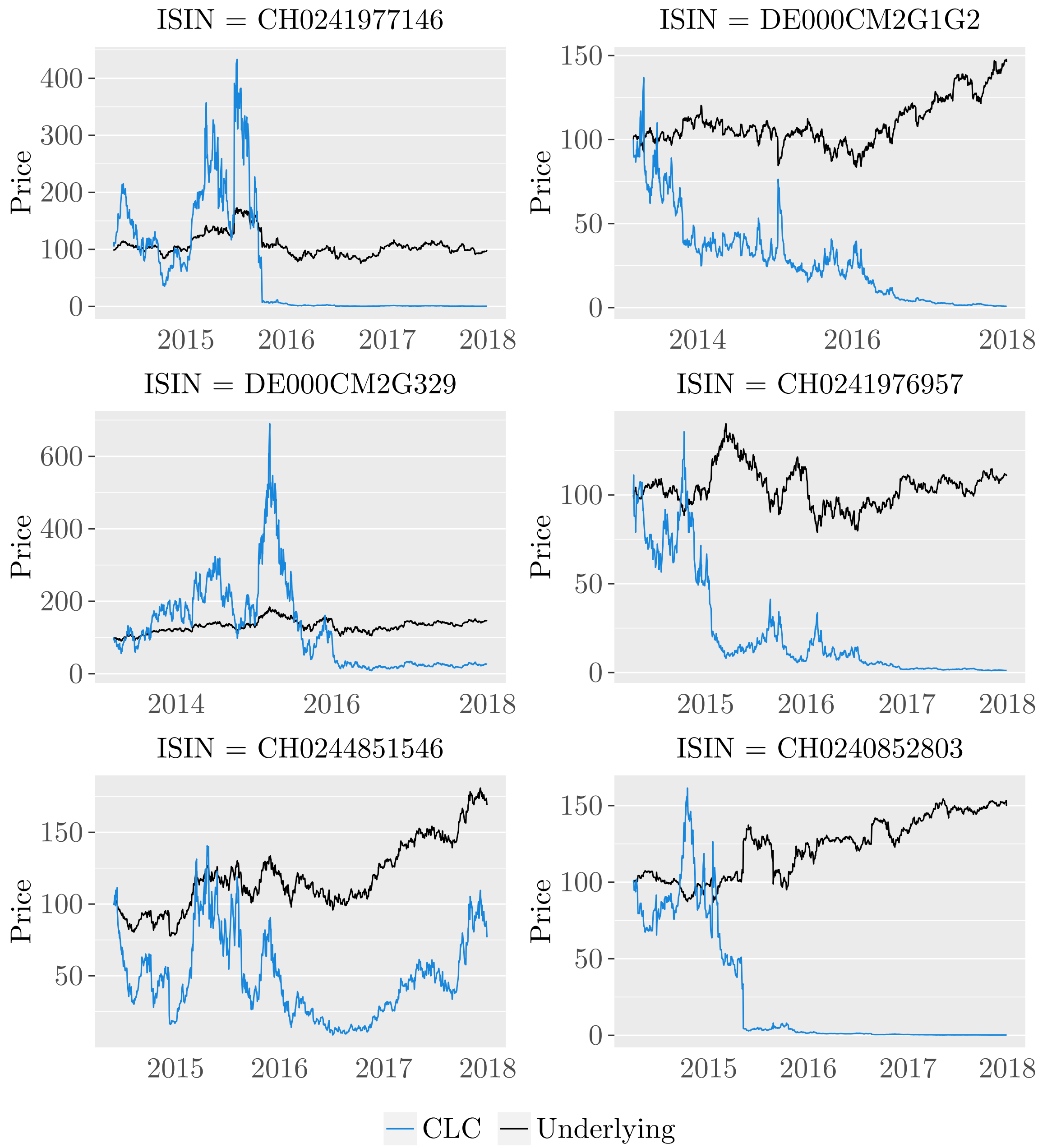


Figure 2.1.1: Price development of randomly chosen CLCs with leverage factors 5 (left) and −5 (right) compared to their underlying assets

intuitive that a long-term upward trend of the underlying results in a favorable development of the price of a CLC with a positive leverage factor. However, following the long-term price paths of arbitrary products, it becomes apparent that this expectation is far from being met. E.g., Figure 2.1.1 shows typical price paths of six random CLCs and their underlying assets. It is very striking that five of six products are close to a total loss. The last product (at the bottom left) has a slightly negative return despite the outstanding performance of its underlying. It seems that product prizes converge to zero in the long run even though the price development of the underlying is favorable. In any case, there is often a huge return deviation between the long-term leveraged return of the underlying and the effective return of the product, especially for products with large leverage factors and long investment periods.

This phenomenon is mainly attributed to the so-called compounding effect but also to accumulated interest and different types of issuer fees. My study reveals the relative importance of the different determinants on the return deviation with an empirical analysis of the most popular CLCs on the Swiss market. Furthermore, based on the pricing formula provided by issuers and previous work on similar products, I derive a model to explain the products' return and its determinants. The model assumes a continuous stochastic process for the underlying asset. Its accuracy is tested using different simulation approaches with constant and time-varying volatility and empirical data. Finally, the distribution of returns over varying holding periods is analyzed. For this purpose, I show the theoretical distribution based on the aforementioned model and compare it with the empirical return distribution. Overall, the main objective of this study is to provide a profound analysis of the risk and return of CLCs, which helps understand why a large number of products suffers losses in the long run and other implications of the daily rebalancing.

The remainder of this chapter is structured as follows. Section 2.2 includes a detailed specification of CLCs, followed by an illustration of the products' hedging and pricing and the compounding effect. A comparison with similar products completes the section. In Section 2.3, related studies are reviewed. Since, to the best of my knowledge, no scientific publications on CLCs have been released so far, the section deals mainly with the performance of similar products. In the following sections, the research design and data are presented. Section 2.6 contains the analysis of the return deviation. The model of the return generating process and its validation is treated in Section 2.7. Subsequently, the return distribution is investigated. The last section concludes.

2.2 Characteristics of Constant Leverage Certificates

2.2.1 Specification

CLCs are categorized as leverage products in the Eusipa derivative map[1]. They are unsecured bonds and thus potentially affected by the default of their issuer. They enable investors to participate disproportionately in price changes of the underlying asset with a constant leverage on a daily basis. A daily price increase of the underlying of $x\%$ results in a price increase of the CLC before interest and issuer fees of $x\%$ multiplied by the product's constant leverage factor. The price computation is based on daily closing prices of the underlying asset. There is a large variety of underlyings available, including currency exchange rates, commodities and futures. Stocks and stock indices, however, are most widely used.

The products can be bought through an exchange or over-the-counter. They have a potentially endless lifetime. However, as usually specified in term sheets, issuers have a right of termination. Investors, on the other hand, have an exercise right but can sell the products also through the exchange. Market making is usually handled by the issuers themselves to ensure the products' liquidity.

Theoretically, the leverage factor can take any real number. Products with positive leverage factors are referred to as "long" CLCs, while products with negative leverage factors are labeled as "short" CLCs. Products with a leverage factor greater than or equal to -1 and less than or equal to 1 are not classified as CLCs. Products with a leverage factor equal to -1 or 1 are known as tracker certificates. Products with a leverage factor between -1 and 1 do not exist on the market for structured products. However, they could be easily replicated by combining tracker certificates with a risk-free asset. Issuers of CLCs typically use integers from -15 to -3 and from 3 to 15 as leverage factor.

Due to the partially very high leverage, there is a substantial risk that the product price drops to zero. With a leverage factor of λ, a price increase or decrease of the underlying of $-\frac{1}{\lambda} \cdot 100\%$ would result in a total loss. In order to prevent this, the products are adjusted over the course of the day to reduce the exposure to the underlying if the price of the underlying

[1]The Eusipa derivative map divides structured products into different categories and provides a payoff profile and brief description for every category to support a uniform categorization among European markets and thus to improve the transparency and understandability of structured products.

hits, undercuts (long CLC) or exceeds (short CLC) a predefined, one-sided barrier. The barrier is typically variable and defined as a percentage of the last closing price of the underlying. The percentage is set between 100% and the closest possible boundary to a total loss of $\frac{\lambda-1}{\lambda} \cdot 100\%$. The specific adjustment approach to a barrier hit differs from issuer to issuer.

One approach is a knock-out mechanism, which is also known from other leverage products. If the price of the underlying hits the barrier (in this case also referred to as stop-loss level), the CLC will be knocked out and redeemed at its current price.

The abrupt end of the investment in case of a knock-out might be perceived as dissatisfying by issuers and investors. For this reason, intraday interventions that do not force a termination of the product are more widely used. The most common approach is what I call "division", where the product is treated as if a new trading day starts whenever the underlying hits the barrier. The following example illustrates this approach.

Assume a long CLC with a leverage factor of 5 and a barrier of 85%. If the price of the underlying drops from 100 to 85 (-15%) before the end of the day, the price of the CLC will drop by $-15\% \cdot 5 = -75\%$ and a new (hypothetical) closing price of the underlying will be set to 85. If the price of the underlying then drops by another -10% to 76.5 until the end of the day, the price of the CLC will drop by another -50%. In that case, the cumulative return of the product amounts to $(1 - 75\%)(1 - 50\%) - 1 = -87.5\%$. Without any intervention over the course of the day, the return would amount to $5 \cdot (76.5\% - 1) = -117.5\%$.

Other adjustment mechanisms are possible as well. E.g., CLCs issued by Goldman Sachs in Germany have a similar proceeding as the knock-out approach. However, if the barrier is hit, the residual value of the product is not redeemed but reinvested again at the end of the day. The product is virtually resting without any exposure to the underlying and its price remains constant until the end of the day. The development of the price of the underlying in the period between the barrier contact and the end of the day has no impact on the product price. An overview of which intraday adjustment approach is applied by which issuer is given in Table 2.2.1.

Which adjustment mechanism is the most favorable for investors cannot be answered in general terms. This is illustrated in Figure 2.2.1, which shows how prices of CLCs with different adjustment approaches change in different scenarios, i.e., with a varying development of the price of the underlying asset. If the underlying of a long CLC continues its downside trend, a

	Division	Knock-out	Stop-loss and reinvest
Citi	•		
Commerzbank	•		
Deutsche Bank	•		
DZ Bank	•		
Erste Group Bank	•		
Goldman Sachs			•
HSBC	•		
HypoVereinsbank	•		
Morgan Stanley[2]		•	
Raiffeisen Centrobank	•		
Société Générale	•		
UBS		•	
Vontobel	•		

Table 2.2.1: Overview of issuers of CLCs in Germany and Switzerland and applied adjustment approaches

knock-out would be desirable. If the underlying follows an upward trend, the division mechanism is the most favorable. The stop-loss and reinvest approach as used by Goldman Sachs is the most favorable alternative if the price of the underlying continues to fall until the next (regular) rebalancing takes place and follows an upward trend afterwards. From an ex ante point of view, however, all three approaches can be considered equally beneficial.

It is rather the height of the barrier that could be crucial for the product value. Due to potentially large price jumps, e.g., overnight jumps or temporary illiquidity of the underlying, the theoretical value of CLCs can drop below zero despite the products' embedded adjustment mechanism. In that case, the investors would suffer a total loss of the investment but would not need to make an additional payment to cover the negative product value. The risk of negative

[2] Morgan Stanley applies the knock-out approach only under a certain condition. A long (short) CLC will be knocked out and redeemed only if the realized selling (purchasing) price of the position in the underlying asset is less (greater) than or equal to the price of the underlying immediately before the barrier is hit or undercut (exceeded). Otherwise the sale (purchase) of the underlying will be undone and the course of the product continues as if the barrier has never been hit or crossed.

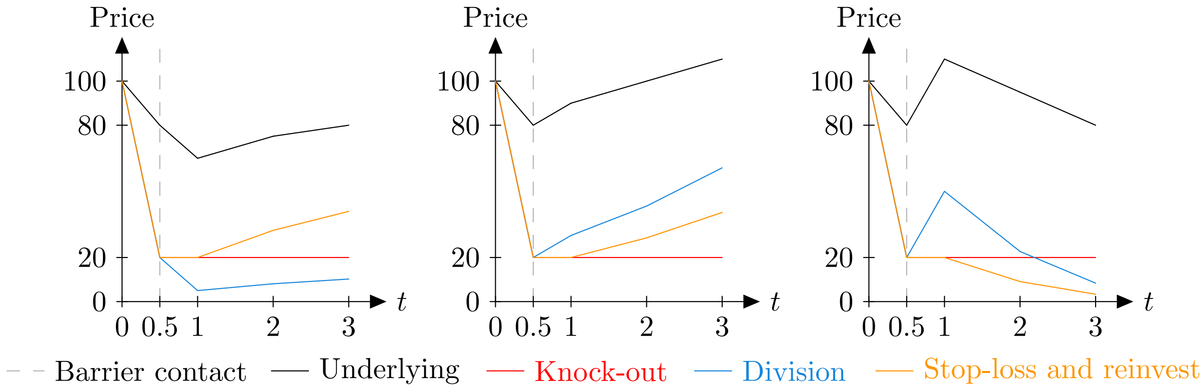


Figure 2.2.1: Comparison of different intraday adjustment approaches. The leverage factor is 4, the barrier is 80% and interest and issuer fees are zero for all products. Rebalancing takes place at $t = 1, 2, 3$.

values resulting from large price jumps of the underlying is taken by the issuers. However, issuers usually set the barrier such that the (absolute) difference between the barrier and the total loss boundary is large enough to avoid this risk or at least to keep it small.

2.2.2 Hedging and Pricing

CLCs can be hedged with a position in the underlying asset, debt (long CLC) and a deposit with the issuer (short CLC).[3] To ensure a leveraged return of λ times the return of the underlying, the position in the underlying needs to correspond λ times the investment amount or the current product price, respectively. A long CLC can be understood as an investment in the underlying asset where a share of $1/\lambda$ is financed with the cash contribution of the investor and a share of $(\lambda - 1)/\lambda$ is financed with debt. On the other hand, a short CLC can be understood as an investment in a risk-free asset where a share of $-1/\lambda$ is financed with cash and a share of $(\lambda - 1)/\lambda$ with the proceeds from the short sale of the underlying. These ratios have to be satisfied at the end of each day to provide a constant leverage on a daily basis. For this reason, the hedge portfolio needs to be rebalanced daily.

In addition, there is a need for rebalancing when the price of the underlying hits the barrier. Long (Short) CLCs with a knock-out approach can be hedged simply by selling (buying) the position in the underlying at the time when a knock-out event occurs. Certificates with a division approach can be hedged by reducing the exposure to the underlying at the time of the barrier

[3]Since CLCs can be replicated without the use of derivatives, they do not conform with the common definition of structured financial products (see, e.g., Rieger, 2016, p. 71). Nonetheless, they are considered as structured products by many banks, investors and the Eusipa.

contact such that the position in the underlying corresponds to λ times the current product price again. The stop-loss and reinvest approach can be hedged by selling (buying) all shares of the underlying and rebalancing in the same manner as before at the end of the day. As indicated above, the hedging strategy can fail independently of the intraday adjustment approach if the price of the underlying changes discontinuously and crosses the barrier with a large jump such that the product value would theoretically fall below zero.

Due to the debt component or deposit, the return of CLCs does not fully correspond to the leveraged daily return of the underlying. It has to be adapted by subtracting (long CLC) or adding up (short CLC) the interest incurred during the day. The interest can be computed by multiplying the debt/deposit amount $CLC_t(\lambda - 1)$ with the daily interest rate $r_t \Delta t$, where CLC_t is the product's last closing price, r_t is the current interest rate and Δt corresponds to one trading day. This allows us to compute the price of a CLC at time $t + 1$ as

$$CLC_{t+1} = CLC_t \left[1 + \lambda \frac{\Delta S_{t+1} + \tau D_{t+1}}{S_t} - (\lambda - 1) r_t \Delta t \right]. \tag{2.1}$$

The term in the squared bracket corresponds to the product's return, where the leveraged return of the underlying (including the tax-adjusted dividend payment τD_{t+1}) is reduced or augmented by the interest component. The interest component reduces the product's return if both λ and r_t are positive or negative. In contrast, the product's return is augmented if only one of the variables is positive and the other negative.

Since Eq. (2.1) leaves no room for profit, issuers apply a slightly modified price-setting formula, which typically incorporates an index fee, a financing spread for long certificates and a short sale fee (or "short rate") for short certificates. The generalized equation

$$CLC_{t+1} = CLC_t \left[1 + \lambda \frac{\Delta S_{t+1} + \tau D_{t+1}}{S_t} - \left[(\lambda - 1) \left(r_t + f_t^{SP} \right) - \lambda f_t^{SR} + f^I \right] \Delta t \right], \tag{2.2}$$

with f_t^{SP} being the financing spread, f_t^{SR} being the short rate and f^I being the index fee, captures most of the price-setting formulas published by issuers for long and short certificates with an index or stock as underlying. Note that I implicitly assume that $f_t^{SP} = 0$ if $\lambda < 0$ and $f_t^{SR} = 0$ if $\lambda > 0$. Both f_t^{SP} and f_t^{SR} can vary over time, while f^I is constant. Depending on the currency of the underlying, issuers typically use the Euro Overnight Index Average (Eonia), the London Interbank Offered Rate (Libor) or similar as interest rate.

The price-setting formula is often published in term sheets or similar documents. However, even though most of the issuers communicate the formula openly, it is often not apparent at first sight whether a specific CLC is attractive compared to other CLCs with similar characteristics, since the notation and structure of the published formulas can differ widely between issuers, asset classes of the underlying and for long and short certificates. Due to the complex and unequal structure of the formulas and the use of many variables and parameters, investors might find it difficult to understand the price setting of these products.

2.2.3 The Effect of Compounding

The price-setting formula provided by issuers, along with daily returns of the underlying assets, allows for a calculation of the products' daily returns. However, it remains unclear how the returns of these products over a period of multiple days are related to the cumulative returns of the underlying assets. A naive expectation could be that the return of the products will equal the leveraged return of the underlying also for periods longer than one trading day. As illustrated with several examples of price paths in Section 2.1, this expectation is not met. CLCs do not reproduce the corresponding leveraged return of the underlying asset over a time period of multiple days.

This return deviation cannot be explained solely with issuer fees and interest; the main reason for the deviation is compounding. This effect is already well-known in connection with fixed income investments, where it leads to an exponential increase in wealth if the earnings from the investment are reinvested. In a broader context, the compounding effect refers to the process of generating or reducing earnings or losses on an asset's previous earnings or losses. While fixed income investments are positively affected by compounding, this is not necessarily the case for CLCs, as I illustrate in the following example. Consider a product with a leverage factor of 5 and assume that the price of the underlying and the price of the product equal 100 at the beginning of the investment period and the risk-free interest and issuer fees equal zero. If the price of the underlying increases to 110 (+10%) on the next day and declines to 100 (-9.09%) on the subsequent day, the price of the product would augment to 150 ($10\% \cdot 5 = 50\%$) on the first day and drop to 81.82 ($-9.09\% \cdot 5 = -45.45\%$) on the second day. The product lost -18.18% in total even though the underlying has a cumulative return of 0%. This return deviation is caused solely by compounding.

In general, the return deviation due to compounding can be determined by subtracting the leveraged cumulative return of the underlying from the target return, which I define as the cumulative product return excluding issuer fees and interest. The target return after two days is calculated as

$$r^T_{0,2} = (1 + r^T_{0,1})(1 + r^T_{1,2}) - 1 = (1 + \lambda r^S_{0,1})(1 + \lambda r^S_{1,2}) - 1, \tag{2.3}$$

where $r^S_{t,t+1}$ is the return of the underlying in the time period from t to $t + 1$. On the other hand, the leveraged cumulative return of the underlying can be expressed as

$$r^N_{0,2} = \lambda r^S_{0,2} = \lambda \left[(1 + r^S_{0,1})(1 + r^S_{1,2}) - 1\right]. \tag{2.4}$$

Note that the leveraged cumulative return is purely generic and fictitious. It is calculated by applying the leverage factor to the cumulative return of the underlying. By subtracting Eq. (2.4) from Eq. (2.3), I obtain

$$\begin{aligned} r^T_{0,2} - r^N_{0,2} &= \left[(1 + \lambda r^S_{0,1})(1 + \lambda r^S_{1,2}) - 1\right] - \lambda \left[(1 + r^S_{0,1})(1 + r^S_{1,2}) - 1\right] \\ &= (\lambda^2 - \lambda) r^S_{0,1} r^S_{1,2}. \end{aligned} \tag{2.5}$$

A positive (negative) return deviation can be interpreted as a favorable (unfavorable) impact of compounding for the holder of the CLC. As Eq. (2.5) shows, compounding is favorable if $r^S_{0,1}$ and $r^S_{1,2}$ are both either positive or negative. The return deviation is further boosted by extreme values for λ, given that none of the values $r^S_{0,1}$ and $r^S_{1,2}$ is zero.

The return deviation after a holding period of more than two days can be derived similarly.

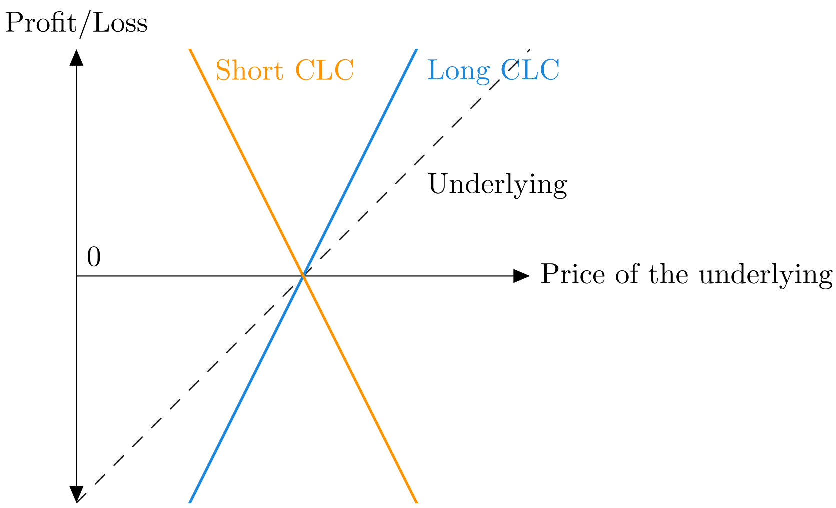


Figure 2.2.2: Payoff diagram of CLCs in the Eusipa derivative map

However, the results and their interpretation become increasingly complex. Nonetheless, it can be concluded that large fluctuations in the price of the underlying negatively affect the product price in the long run. The compounding effect is favorable in periods of monotonically increasing or decreasing prices and unfavorable in periods of high volatility.[4]

Another implication of the compounding effect is that the cumulative return of the underlying is not sufficient to determine the price of a CLC after a holding period of multiple days. As is apparent from Eq. (2.5), the series of daily returns that occurred during the investment period are required as well.[5] For this reason, CLCs are characterized as path-dependent and cannot be illustrated in the common payoff diagram for structured products, where the product's profit or loss is displayed as a function of the price of the underlying at the end of the investment period. Nevertheless, this is often done in practice. E.g., Figure 2.2.2 shows the payoff diagram of CLCs in the Eusipa derivative map. The diagram suggests that the product price at the end of the investment period can be expressed as a simple linear function of the price of the underlying, which can potentially mislead investors and result in inaccurate expectations.

2.2.4 Comparison with Related Instruments

CLCs are not the only instruments that allow investors to benefit from a leveraged return of the underlying. The most common alternative are options and warrants. They give their holder the right to buy (call option) or sell (put option) an underlying asset at a predefined price (strike or exercise price) until (American option) or at (European option) a predefined point in time. Their price depends not only on the price of the underlying asset but also on its volatility and time to maturity.

Another alternative investment product are endless leverage certificates (ELCs).[6] The outstanding volume of ELCs was roughly EUR 900 millions in Germany in 2019, which is roughly two to three times more than for CLCs (Eusipa, 2019b). Similar to CLCs, ELCs are (potentially) open-ended and designed to gain a leveraged return due to low capital investment. The main difference is that the return of ELCs is not constant on a daily basis but corresponds

[4]However, a favorable impact of the compounding effect on the performance of a CLC does not imply that the CLC achieved a positive (cumulative) return and vice versa. E.g., if the price of the underlying decreases monotonically, the compounding effect is favorable because it decelerates the price drop. Nonetheless, the return of the product is negative.

[5]As I show in Section 2.7, the price of a CLC can be approximately determined with the realized variance of the underlying as input parameter instead of daily returns.

[6]ELCs are sometimes also referred to as mini futures or open-end turbos.

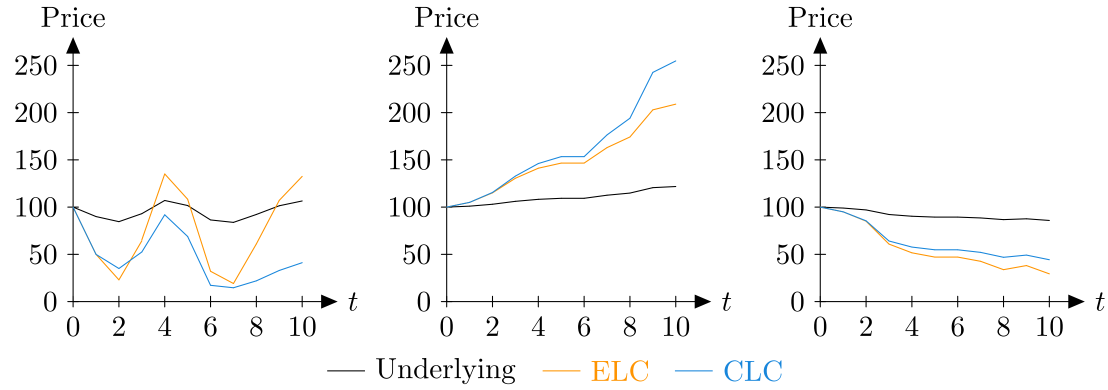


Figure 2.2.3: Comparison of the performances of a ELC and a CLC in different scenarios

approximately to the leveraged long-term return of the underlying.[7] This can be achieved by not rebalancing the hedging portfolio at any time during the product's lifetime.

The price of ELCs is defined simply as the difference between the value of the underlying and the product's predefined financing level. The financing level is slightly adapted after each day to redeem accruing interest and a credit spread in favor of the issuer. In contrast to CLCs, the financing level does not vary as a function of the price of the underlying. For this reason, ELCs are not path-dependent. Their price at the end of the holding period can be computed just based on the cumulative return of the underlying. For this reason, ELCs can be easily displayed in a payoff diagram, which looks exactly the same as the misleading payoff diagram for CLCs shown in Figure 2.2.2. ELCs also have a barrier with the same function as for CLCs to prevent negative prices. It is usually slightly greater (long ELC) or smaller (short ELC) than the financing level. If the underlying breaches the barrier, the product is knocked out and redeemed at its current price (Entrop et al., 2009; Rossetto and Van Bommel, 2009).

Figure 2.2.3 shows a comparison of the performances of a ELC and a CLC with the same initial leverage and underlying in different scenarios, i.e., with a varying development of the price of the underlying. ELCs perform better when the price of the underlying is very volatile and moves sideways. They can recover quickly from temporary low stock prices as long as the barrier is not crossed. In return, CLCs are more favorable in periods of monotonic positive or negative trends.

Leveraged exchange-traded funds (LETFs) also incorporate the idea of constant leverage. These products are publicly traded mutual funds with the goal to track an index, a basket of

[7] The product's return slightly deviates from the leveraged return of the underlying due to interest and issuer fees.

	Warrants	ELCs	LETFs	CLCs
Daily leverage	Variable	Variable	Constant	Constant
Term	Limited	Open-ended	Open-ended	Open-ended
Path-dependant	No	No	Yes	Yes
Adjustment approach	None	Knock-out	None	Mostly division

Table 2.2.2: Comparison of characteristics of CLCs and other leveraged products

stocks or another exchange-traded fund (ETF) with a leveraged return on a daily or monthly basis (Cheng and Madhavan, 2009; Avellaneda and Zhang, 2010; Charupat and Miu, 2011). They are a relatively popular leverage instrument with roughly USD 40 billions assets under managements globally (Etf.com, 2019). Apart from the fact that LETFs are funds and CLCs are certificates, the two assets have very similar risk and return characteristics. Nonetheless, there are some essential differences for investors. LETFs usually have a leverage factor between -3 and 3, while the leverage factor of CLCs is typically much more extreme. As a result, CLCs might attract more speculators that are focused on short-term investments. In addition, CLCs are available for a wider variety of different underlying assets (such as single stocks, commodities and futures). For this reason, they are better suited to meet specific needs of investors.

An overview of the comparison of the above named related products is given in Table 2.2.2.

2.3 Literature Review

While there are, to my best knowledge, no scientific publications on CLCs, different studies with similar research objectives have been conducted on related products. In the following, I review the most important studies on the performance, return deviation and pricing of ELCs and LETFs.

2.3.1 Endless Leverage Certificates

Wilkens and Stoimenov (2007) were among the first to examine the pricing of leveraged structured products. They analyzed so-called (classic) turbos, the predecessors of ELCs. The characteristics of these products are similar to those of ELCs; they also allow investors to participate overproportionally in the performance of their underlying asset in a futures-like manner but with a limited lifetime. Wilkens and Stoimenov (2007) observed distinct overpricing. They found that ask prices of long certificates exceeded the theoretical fair value by 4.26% and ask prices of short certificates exceeded the fair value by 7.13% on average. They supposed that the lower premiums for long certificates are related to lower hedging costs for issuers.

The first study on ELCs was conducted by Entrop et al. (2009). They analyzed the price-setting formulas of different issuers according to which they are willing to sell the products over time and found that the formulas are strongly designed in favor of the issuers. E.g., holding a long ELC with the German stock index (DAX) as underlying for one year resulted in a profit potential, defined as the deviation between the fair value and the price of the product, of 5-10% of the product's price for the issuer. The profit potential was increasing over the products' holding time, which is consistent with the life cycle hypothesis for structured products (see Stoimenov and Wilkens, 2005). Furthermore, they found that the financing level and knock-out probability are the main drivers of the profit potential.

Unlike Entrop et al. (2009), Rossetto and Van Bommel (2009) used endogenous holding periods in their valuation model. They found that the fair value of a typical ELC with a DAX stock as underlying was approximately 0.3% above the intrinsic value. ELCs with a more volatile underlying can be worth even more due to higher gap risk and limited liability. After analyzing quoted prices of ELCs written on DAX stocks, they found that midquotes were on average 0.67% greater than the corresponding intrinsic values, which indicates that the products were slightly overpriced.

Entrop et al. (2012) examined the pricing of ELCs on government bond futures and arrived at the same conclusion that issuers can realize significant profits due to increasing financing levels especially when investors hold the products for longer periods. However, gap risk can decrease the profit potential even below zero due to jumps in the interest rate dynamics.

2.3.2 Leveraged Exchange-Traded Funds

Avellaneda and Zhang (2010), Giese (2010) and Jarrow (2010) were among the first to study the implications of periodical rebalancing on the long-term risk and return characteristics of LETFs analytically using a mathematical framework. The authors independently derived a model to describe the return of a LETF over any holding period as a function of the return of the underlying. Assuming that the underlying follows a geometric Brownian motion and that the portfolio is rebalanced continuously, the long-term return of LETFs can be calculated exactly. They found that the logarithmic return of LETFs basically corresponds to the logarithmic return of the underlying multiplied by the leverage factor minus a discount, which depends on the realized variance of the underlying, the expense ratio of the fund, the interest rate and the short rate.[8] Giese (2010) went a step further and analyzed the profit and loss probability distribution. He found that the skewness is increasing with the leverage factor, the volatility of the underlying and the holding period. For very large values of these three parameters, the loss probability tends to one even though the expected return tends to infinity. Avellaneda and Zhang (2010) also tested whether their model holds empirically and found a high degree of conformity.

Next to the above-mentioned rather theoretical studies, a lot of research has been conducted on the historical performance of LETFs. Lu et al. (2009) analyzed the performance of LETFs over different holding periods and found that over a holding period no longer than one month the return of these funds is not significantly different from the leveraged return of their underlyings. However, the return deviation can be huge, especially for short funds, if the investment horizon is longer. Also, the realized variance and autocovariance of the underlying are found to have a significant impact on the return of LETFs.

Similar results were found by Murphy and Wright (2010) for commodity-based LETFs. The authors confirmed that these funds are able to track the leveraged underlying return on a daily basis. However, there were relatively large return deviations over long-term investment horizons. Two thirds of the funds were negatively affected by compounding over their life time of two to three years. More than 80% of the funds underperformed their underlying.

The findings of Lu et al. (2009) and Murphy and Wright (2010) are in line with the performance analysis of Charupat and Miu (2011). In addition, Charupat and Miu (2011) analyzed the trading statistics and pricing efficiency of LETFs. They found that deposits in these funds had a much smaller investment horizon and investment amount than conventional ETFs. The deviation between the funds' closing prices and the corresponding net asset values at the end of the day was small on average but had a greater volatility compared to conventional ETFs.

Tang and Xu (2013) studied the determinants of the return deviation between the actual return of LETFs from the leveraged cumulative return of their underlyings. They split the

[8] A similar derivation is shown in Section 2.7.1 for CLCs.

return deviation into a compounding and a noncompounding component and found that the compounding and noncompounding deviations both increase with longer holding periods and that the noncompounding deviation was at least as important as the compounding deviation with an investment period of up to forty days. They further split the noncompounding deviation into two additional components. The first component is the deviation between the funds' closing prices and net asset values, for which they found the Libor to be the key driver. The second component is a residual deviation, which is mainly affected by the return of the underlying. The expense ratio of the LETFs analyzed by Tang and Xu (2013) ranges between 0.91% and 0.95% excluding variable costs.

Loviscek et al. (2014) and Bansal and Marshall (2015) analyzed the long-term performance of hypothetical LETFs with different leverage factors and rebalancing frequencies using a simulation approach. The returns of the funds were calculated based on real-world data, starting with the inception of the Dow Jones Industrial Average (DJIA) index in 1896 and the inception of the Standard & Poor's (S&P) 500 index in 1964 respectively. Both studies found a positive return deviation also for holding periods of one year or longer and concluded that compounding does not negatively impact buy-and-hold investors. These findings are contradictory to prior research. The authors argued that the other empirical studies were done a few years after the inception of LETFs, which was a period of high market volatility associated with the financial crisis, resulting in a negative impact of compounding. To explain the discrepancy from the theoretical studies, Loviscek et al. (2014) showed that the distribution of real-world returns is – as opposed to the assumed distribution in the theoretical models of Avellaneda and Zhang (2010), Giese (2010) and Jarrow (2010) – not normal but much more leptokurtic. The higher density of the distribution around the positive mean results in a positive impact of compounding. They also argued that the incorporation of management fees does not change the main conclusion of their paper because the fee-adjusted cumulative returns of LETFs are still higher than the leveraged cumulative return of the underlying.

In summary, it can be said that LETFs have been blamed in most of the scholarly articles for performing poorly over a longer time horizon and for not being suited as long-term investment due to the negative impact of compounding. However, a few newer studies defended LETFs and criticized that some results are based on unrealistic assumptions on the return distribution of the underlying or data from the financial crisis when market volatility was relatively high.

But irrespective of the impact of compounding, it can be stated that the expense ratio of LETFs excluding the funds' variable costs (around 0.95%) is very high compared to their ETF counterparts (0.095%–0.2%) (Tang and Xu, 2013, p. 317).

2.4 Research Design

The objective of my study is to provide a thorough analysis of risk and return of CLCs with three different approaches. The first approach in Section 2.6 is all about the return deviation between the products' effective returns and the leveraged cumulative returns of the underlyings. In particular, I examine whether there is indeed a deviation to the disadvantage of investors on average based on historical data. The second question addressed in the first approach is to what extent different determinants contribute to this deviation. As illustrated in Section 2.2.3, the most striking determinant is compounding. The other components of the return deviation are interest and issuer fees. The price-setting formula allows for an individual investigation of the impact of these three components of the return deviation. Furthermore, the return deviation and its components are analyzed for varying holding periods and leverage factors.

In the second approach in Section 2.7, a general model is derived that explains the long-term return of CLCs as a function of the cumulative return of the underlying and other variables. The model is based on the groundwork of Avellaneda and Zhang (2010), Giese (2010) and Jarrow (2010) on LETFs but is adapted due to additional components in the pricing formula of CLCs. The main assumptions are that rebalancing takes place continuously and that the price of the underlying follows a geometric Brownian motion.

Since these assumptions might be unrealistic in practice, the model is tested using different methods. The first test reveals whether the assumption of continuous rebalancing leads to inaccurate model predictions. The test is carried out by calculating discrete, daily returns of the underlying assets using a geometric Brownian motion with constant volatility. The drift and volatility terms of the geometric Brownian motion correspond to the mean daily return of the underlying and its volatility in the period from the product's issuance to the end of the investigation period. The second test checks the geometric Brownian motion assumption by introducing time-varying volatility using a generalized autoregressive conditional heteroscedasticity (GARCH) model. This approach results in heavier tails in the return distribution, which are characteristic of real-world stock returns. The closest approximation to reality is, however, achieved with the last test, which is carried out with historical returns of the underlying.

All tests undergo a regression analysis with the same regression models. These regression models basically correspond to the theoretical model with different terms being grouped and assigned to a regression coefficient. The last regression model measures the model error relative to the cumulative return of the products. The regressions are performed for different investment horizons. Since in my simulations the drift and volatility terms of the geometric Brownian motion correspond to the historical mean daily return of the underlying and its volatility in the period from the product's issuance to the end of the investigation period, a better comparability of the results from the simulations and empirical analysis is ensured.

The third approach in Section 2.8 addresses the question of the shape of the return distribution of CLCs. The distribution is first analyzed theoretically under the same assumptions as in the return model. To verify whether the theoretical distribution applies in practice, it is compared to historical return distribution. Since the effect of compounding on the return of the certificates can vary for different investment horizons, the return distribution after multiple holding periods is analyzed. For this purpose, the period from the issuance of the individual products to the end of the sample period is divided into non-overlapping intervals.

To conduct my analysis, I received daily closing prices of CLCs from the Swiss exchange. But while there is a huge variety of CLCs on the Swiss exchange, the trading frequency of individual products is rather low compared to other asset classes. Most of the products are not traded every day and, as a result, the data is incomplete. Also, if price information is available on a particular day, it is still unclear whether the close price reflects the product value at the end of the day, since the close price corresponds to the last price traded. Given the low trading frequency of CLCs, the last trade could be made hours before the end of the trading time when the product had a much different value (CLCs with high leverage in particular).

For this reason, the daily closing prices of CLCs used in all three approaches are calculated based on the price-setting formula provided by the issuers (see Eq. (2.2)).[9] Prices of underlying assets required for the calculation are retrieved from Thomson Reuters Eikon. The returns of the underlying assets are based on the total return, where dividend payments are incorporated. The daily quotes of the reference interest rates are taken from different sources but mostly from the central bank of the respective currency. The other parameters required to calculate the product

[9] A similar approach was applied by Entrop et al. (2009) for ELCs.

price, namely the leverage factor, the reference interest rate, the financing spread, the short rate and the index fee, were provided by the Swiss exchange or retrieved from the products' term sheets. Furthermore, I do not capture the currency mismatch between the underlying and product, i.e., product prices are calculated as if they were issued in the currency of the underlying. This allows us to abstract from noise in the calculation of (the determinants of) the return deviation. Finally, for the sake of simplicity, products are excluded from the sample if the close price of the underlying is below the barrier level at any point of time during the investigation period. A correct implementation of the intraday adjustment approach in case of barrier events would require to monitor the intraday price development of the underlying assets.

The calculation of product prices based on the price-setting formula has two limitations. First, in term sheets of some products it can be found that the financing spread and short rate may change over time without further specification of the time of the change or the new amount of the fee. In my analysis, I assume a constant financing spread and short rate corresponding to the amount at issuance of the product. Second, the tax rate is often not clearly communicated by issuers. In some term sheets, it is mentioned that a tax-adjusted dividend is added to the return without specifying the tax rate. In other term sheets, the tax rate at issuance is specified, but issuers reserve the right to change it at any time during the product's lifetime. Consequently, I assume a dividend tax rate of 0%, which is implicitly applied by using the total return of the underlying assets. These limitations could be avoided by using prices from exchanges. However, the trading frequency problem related to using these prices is much more important such that the application of calculated prices based on the price-setting formula is much more accurate.

2.5 Data

2.5.1 Sample Selection

This research study is based on CLCs issued in Switzerland. The investigation period starts at the beginning of 2013 and lasts until the end of 2017. I do not consider older data because the market for CLCs was very small at that time with only few products available. In 2013, the market emerged with 56 new CLCs issued by Commerzbank. The breakthrough came in 2014 with the market entry of Vontobel. 332 of these certificates were launched in that year.

In my analysis, only CLCs with an equity or index as underlying asset are considered.

Products with futures, commodities, currencies or interest rates as underlying are excluded from the sample because they have a differing pricing formula, which would require a separate analysis, and the prices of these underlyings are often not available. Equities and indexes are also the most popular underlying assets for CLCs. Using data provided by SIX Swiss exchange, I further filter the most popular CLCs based on trading frequency, i.e., products are only included in the sample if they have at least 100 trades during the investigation period. The final sample consists of 339 CLCs.

2.5.2 Descriptive Statistics

Figure 2.5.1 gives an overview of the product characteristics of the sample. One third of the products was issued by Commerzbank and two thirds were issued by Vontobel. Long certificates, which account for 64% (218) of the sample, are more popular than short certificates. 76% of the long certificates have a leverage factor of either 4, 5 or 6. Among the short certificates, the leverage factors -4, -5 and -6 are most frequently chosen. Other popular leverage factors are 10 and -10. Almost all products are traded in CHF, with a few exceptions in EUR and USD. However, that does not apply to the underlying assets, where only 34% are listed in CHF. 43% of the underlying assets are traded in EUR and 19% are traded in USD. Other currencies in the sample are GBP, JPY and NOK. Equities account for 72% of the underlyings. However, the most popular single underlyings are indexes. DAX, DJIA, Euro Stoxx 50, Nasdaq 100 and S&P 500 are chosen most often and account for at least 3.2% each. The most frequent underlying equities are Swatch, UBS and Volkswagen with a share of 2.4% to 2.6%. The sample contains 94 different underlyings in total, none of which accounts for more than 5% of the sample. More detailed descriptive statistics are included in Appendix A.1.

The index fee varies from 0.7% to 1.5% with a mean of roughly 1%. The mean financing spread and short rate amount to 0.4% and 0.7% respectively and have relatively large fluctuations. The minimum value of both variables is 0.1%, while the maximum financing spread is 2.5% and the maximum short rate is 25%[10]. Commerzbank has a lower index fee than Vontobel on average (0.7% versus 1%). However, products issued by Commerzbank typically have a much higher financing spread (0.97% versus 0.14%) and short rate (1.06% versus 0.46%) than

[10]The short rate of 25% is associated with a short certificate on the company Seadrill, which suffered a massive price decline in the period from 2015 until 2017 when they filed for bankruptcy. The value is far above the short rate of any other product.

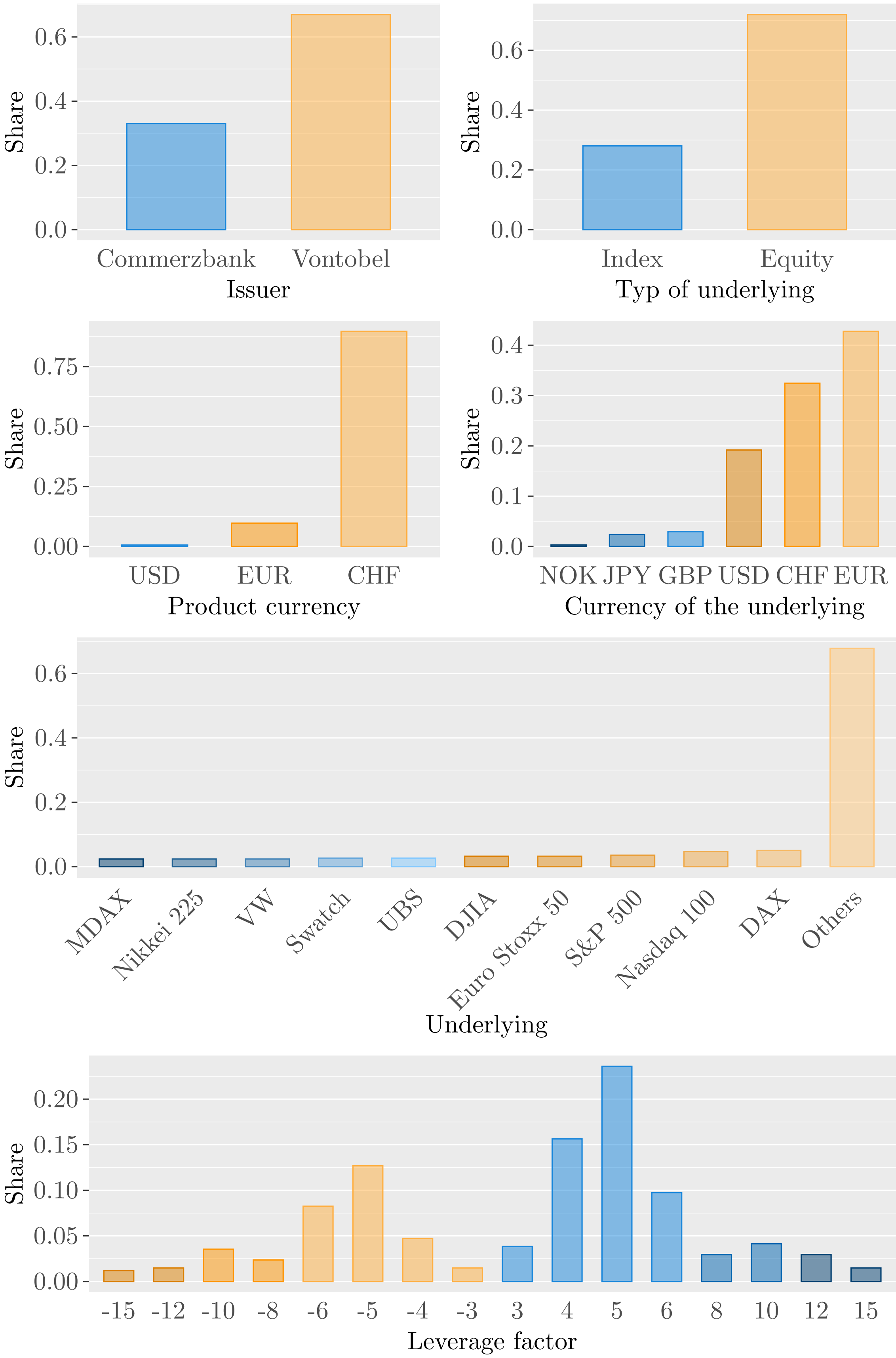


Figure 2.5.1: Sample statistics

Vontobel products. Since the impact of the financing spread and short rate is amplified by the leverage factor, differences in the index fee play a less important role. From this perspective, Vontobel seems to have fairer conditions.[11] A table with further statistics on issuer fees can be found in Appendix A.2.

2.6 Return Deviation and Its Determinants

CLCs are designed to provide a multiple of the return of their underlying assets on a daily basis. As illustrated in Section 2.2.3, there can be large deviations between the products' return and the leveraged return of their benchmarks over long-term investment periods. In this section, this return deviation is studied based on empirical data over different holding periods. The return deviation is furthermore split into multiple components to determine the extent to which these individual determinants contribute to the total return deviation.

2.6.1 Definition of the Return Deviation Components

I define the total return deviation, denoted by $r_{0,t}^{E-N}$, over an investment period of length t as the difference between the product's return $r_{0,t}^{E}$ and the leveraged cumulative return of the underlying $r_{0,t}^{N}$ as follows.

$$r_{0,t}^{E-N} = r_{0,t}^{E} - r_{0,t}^{N} \tag{2.6}$$

Denote by $r_{0,t}^{F}$ the return if no issuer fees would occur and by $r_{0,t}^{T}$ the return if neither issuer fees nor interest would occur. Then, the total return deviation can be decomposed into three determinants according to

$$r_{0,t}^{E-N} = r_{0,t}^{E-F} + r_{0,t}^{F-T} + r_{0,t}^{T-N}, \tag{2.7}$$

$$\begin{aligned} \text{with} \quad r_{0,t}^{E-F} &= r_{0,t}^{E} - r_{0,t}^{F}, \\ r_{0,t}^{F-T} &= r_{0,t}^{F} - r_{0,t}^{T}, \\ \text{and} \quad r_{0,t}^{T-N} &= r_{0,t}^{T} - r_{0,t}^{N},. \end{aligned}$$

[11] Note that this assessment is only indicative. The products of the two issuers cannot be directly compared to each other due to different underlyings, which may have differing borrowing and currency hedging costs.

$r_{0,t}^{E-F}$ is the return deviation due to issuer fees, $r_{0,t}^{F-T}$ is the return deviation due to interest and $r_{0,t}^{T-N}$ is the return deviation due to the compounding effect. The superscripts E, F, T and N stand for "effective return", "fair return", "target return" and "naively expected return". The latter term is coined by the literature on LETFs due to the naive expectation that the products' return corresponds to the leveraged return of the benchmark also for long-term investment periods, which some investors might have. The formulas are designed in a way that a negative (positive) sign of any return deviation component can also be interpreted as a negative (positive) impact of the respective component on the effective return. The different types of return are calculated as

$$
\begin{aligned}
r_{0,t}^{E} &= \frac{CLC_t - CLC_0}{CLC_0} \\
&= \prod_{j=0}^{t-1}\left[1 + \lambda\frac{\Delta S_{j+1} + \tau D_{j+1}}{S_j} - \left((\lambda - 1)\left(r_j + f_j^{SP}\right) - \lambda f_j^{SR} + f^I\right)\Delta t\right] - 1, \quad (2.8)\\
r_{0,t}^{N} &= \lambda\frac{\sum_{j=0}^{t-1}\Delta S_{j+1} + \tau D_{j+1}}{S_0}, \quad (2.9)\\
r_{0,t}^{T} &= \prod_{j=0}^{t-1}\left(1 + \lambda\frac{\Delta S_{j+1} + \tau D_{j+1}}{S_j}\right) - 1, \quad (2.10)\\
\text{and} \quad r_{0,t}^{F} &= \prod_{j=0}^{t-1}\left[1 + \lambda\frac{\Delta S_{j+1} + \tau D_{j+1}}{S_j} - (\lambda - 1)r_j\Delta t\right] - 1. \quad (2.11)
\end{aligned}
$$

These equations are, with the exception of $r_{0,t}^{N}$, based on the pricing formula in Eq. (2.2).

2.6.2 Relative Importance of the Return Deviation Components

The return deviation and its components, as defined in the previous section, are calculated for all CLCs in the sample and for different holding periods. An illustration of the main results is displayed in Figure 2.6.1. The figure shows mean values for the different return types and for the return deviation (components) over different holding periods. The mean values are displayed for the overall sample but also for sub-samples including only products with a specified leverage factor.

The mean effective return ($r_{0,t}^{E}$) of the overall sample over a holding period of one day is 0.1%. The mean return increases with a larger holding period. An investment over 365 days results in a mean return of 18.3%. Also, products with a large leverage factor perform better on average. For instance, products with a leverage factor of −10 have a mean return of −91.1%, while products with a leverage factor of 10 have a mean return of 167.3% after one year.[12]

The total return deviation ($r_{0,t}^{E-N}$) is negligible for very short investment periods. After 30 days the average of the overall sample amounts to -1.1% and increases to -20.4% for holding periods of one year. However, these values come along with a large standard deviation, which is 4 to 10 times larger than the mean. Also, when comparing the outcome between products with varying leverage, it is difficult to see a uniform picture. Most of the leverage levels are attended by a negative return deviation; however, no clear trend is apparent with increasing or decreasing leverage. The long-term return deviation and its large variance is mainly attributed to the effect of compounding ($r_{0,t}^{T-N}$), which is responsible for a return deduction of 17.4% over a holding period of one year. I conclude that the magnitude of the return deviation is boosted with increasing holding period or leverage factor mainly due to the compounding effect, but based on empirical data, it is difficult to determine whether compounding has a positive or negative impact on the product performance on average.

A clearer picture emerges from the analysis of the return deviation due to issuer fees ($r_{0,t}^{E-F}$). Its mean amounts to -3.2% after a holding period of one year for the overall sample. This value is far above the expense ratio of LETFs of around 0.95% (see Tang and Xu, 2013) but can be partially justified with the higher leverage in CLCs. Issuer fees seem to be high in particular for products with very high leverage. For instance, they account for a mean return deduction of 6.4% when holding CLCs with a leverage factor of 10 for one year. Since the short rate is amplified with an increasingly negative leverage, one could also expect increasing issuer fees for products with extreme negative leverage. However, this can only be confirmed for a holding period of up to 90 days. Due to the extremely poor long-term performance of these products, the product value virtually shrinks to zero such that the charged fees are relatively small compared to the initial investment amount. Hence, investors and issuers have aligned interests, as a well-performing product results in enhanced earnings for issuers.

While increasing issuer fees always have a negative impact on the return, this is not necessarily the case for the interest component ($r_{0,t}^{F-T}$). During the investigation period, the interest level was exceptionally low. Depending on the currency of the underlying, the interest rate was slightly positive or negative. As a result, interest contributes to a minor fraction of the total return deviation and has the smallest impact compared to the other components in my results.

[12]Even more extreme returns can be observed for products with a leverage factor of -15, -12, 12 or 15. However, the results for long holding periods may not be representative due to the small sample size.

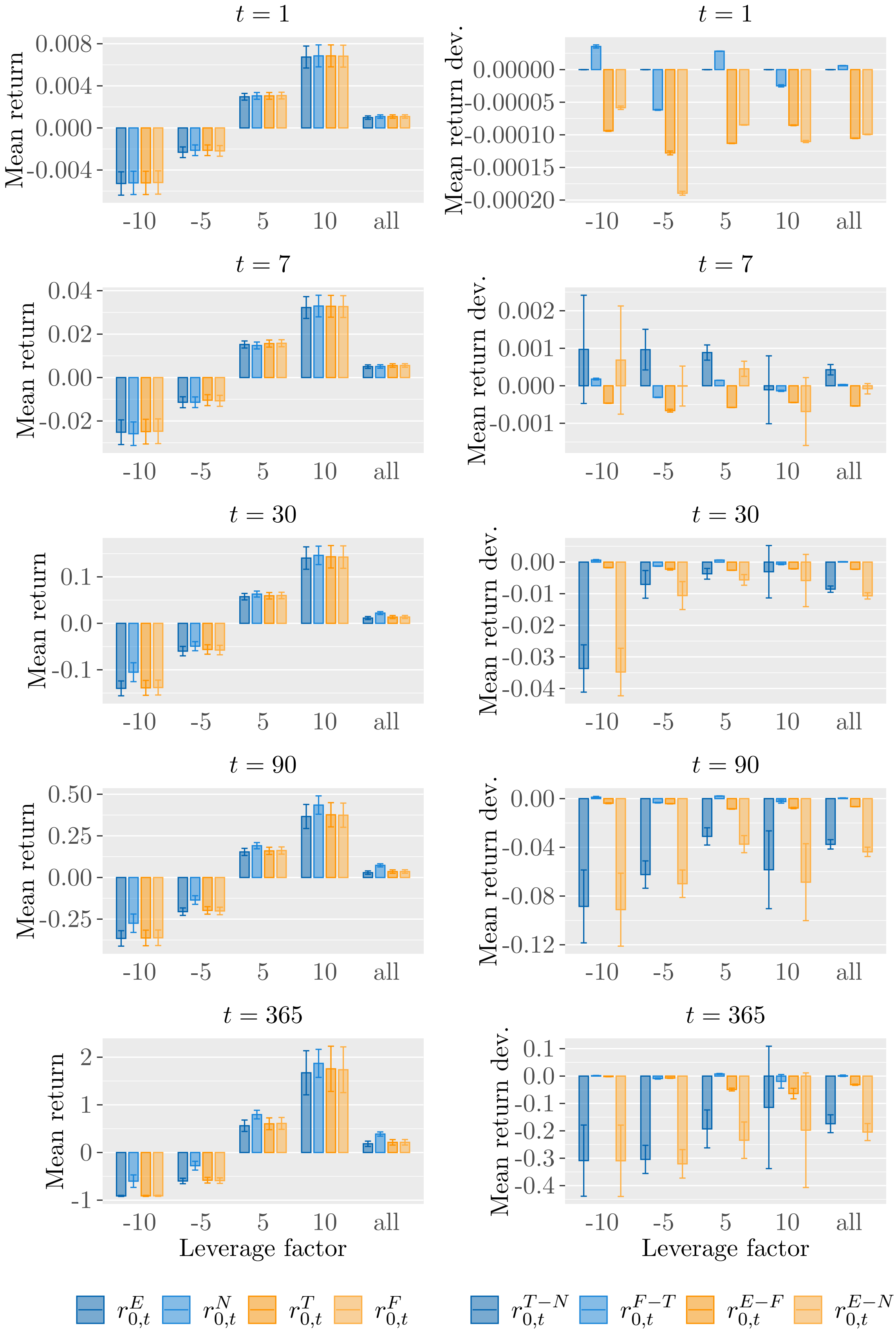


Figure 2.6.1: Mean returns (left) and mean return deviations (right) over different holding periods. t corresponds to the holding period including non-trading days. The error bars indicate the standard error.

The mean return deviation due to interest is 0.1% over a period of one year for the overall sample, which implies that the debt or deposit component in CLCs increases the products' return. Again, there is no uniform result among different leverage levels of long or short certificates, but the magnitude is enhanced with increasing holding period.

2.7 Return Generating Process

As shown empirically in the previous section, compounding can have a positive or negative impact on the return of CLCs. Even though the product's return is related to the return of the underlying, e.g., a long CLC can still have a negative return in the long run despite the positive return of the underlying. This example shows that the implications of the daily rebalancing feature in CLCs are not trivial. In the first part of this section, to increase the understanding for the relation between CLCs and their underlying, I derive a model that explains the product's return as a function of the return of the underlying. The second part tests whether the model provides accurate results under more realistic conditions that are not consistent with the model's core assumptions.

2.7.1 A Theoretical Model

I assume that the underlying asset follows a geometric Brownian motion, i.e., the price of the underlying S_t satisfies the stochastic differential equation

$$\frac{dS_t}{S_t} = \mu dt + \sigma dW_t, \tag{2.12}$$

where μ is the return, σ is the return volatility and W_t is a standard Brownian motion. According to Itô's lemma, the differential of a twice differentiable function $f(S_t, t)$ is given by

$$df = \left(\frac{\partial f}{\partial S_t} \mu S_t + \frac{\partial f}{\partial t} + \frac{1}{2} \frac{\partial^2 f}{\partial {S_t}^2} \sigma^2 {S_t}^2 \right) dt + \frac{\partial f}{\partial S_t} \sigma S_t dW_t. \tag{2.13}$$

By applying Itô's formula in Eq. (2.13) to $f(S_t, t) = \ln S_t$, the following solution of Eq. (2.12) is obtained.

$$\begin{aligned} d \ln S_t &= \left(\frac{1}{S_t} \mu S_t - \frac{1}{2} \frac{1}{{S_t}^2} \sigma^2 {S_t}^2 \right) dt + \frac{1}{S_t} \sigma S_t dW_t \\ &= \left(\mu - \frac{1}{2} \sigma^2 \right) dt + \sigma dW_t. \end{aligned} \tag{2.14}$$

According to the pricing formula of CLCs given in Eq. (2.2), the return of these products is defined as

$$\frac{dCLC_t}{CLC_t} = \lambda \frac{dS_t}{S_t} + \left[(1-\lambda) \left(r_t + f_t^{SP} \right) + \lambda f_t^{SR} - f^I \right] dt. \tag{2.15}$$

Note that the dividend term is removed because I consider the return of the underlying $\frac{dS_t}{S_t}$ as the total return including dividends in the subsequent analysis. Substituting $\frac{dS_t}{S_t}$ according to Eq. (2.12), I obtain

$$\begin{aligned}
\frac{dCLC_t}{CLC_t} &= \lambda \mu dt + \lambda \sigma dW_t + \left[(1-\lambda) \left(r_t + f_t^{SP} \right) + \lambda f_t^{SR} - f^I \right] dt \\
&= \left[\lambda \mu + (1-\lambda) \left(r_t + f_t^{SP} \right) + \lambda f_t^{SR} - f^I \right] dt + \lambda \sigma dW_t \\
&= \tilde{\mu}_t dt + \tilde{\sigma} dW_t,
\end{aligned} \tag{2.16}$$

$$\begin{aligned}
\text{with} \quad & \tilde{\mu}_t = \lambda \mu + (1-\lambda) \left(r_t + f_t^{SP} \right) + \lambda f_t^{SR} - f^I \\
\text{and} \quad & \tilde{\sigma} = \lambda \sigma.
\end{aligned}$$

The price process in Eq. (2.16) is basically a geometric Brownian motion for the CLC with adapted values for the return and the volatility. Itô's formula for $f\left(CLC_t, t\right) = \ln CLC_t$ gives the following solution.

$$\begin{aligned}
d \ln CLC_t &= \left(\tilde{\mu}_t - \frac{1}{2} \tilde{\sigma}^2 \right) dt + \tilde{\sigma} dW_t \\
&= \left[\lambda \mu + (1-\lambda) \left(r_t + f_t^{SP} \right) + \lambda f_t^{SR} - f^I - \frac{1}{2} \lambda^2 \sigma^2 \right] dt + \lambda \sigma dW_t.
\end{aligned} \tag{2.17}$$

I multiply Eq. (2.14) by λ and subtract it from Eq. (2.17) to obtain

$$d \ln CLC_t - \lambda d \ln S_t = \left[\frac{\lambda - \lambda^2}{2} \sigma^2 + (1-\lambda) \left(r_t + f_t^{SP} \right) + \lambda f_t^{SR} - f^I \right] dt. \tag{2.18}$$

Considering the investment horizon $[0, t]$, dt becomes t, $d \ln CLC_t$ becomes $\ln CLC_t - \ln CLC_0$ and $d \ln S_t$ becomes $\ln S_t - \ln S_0$. By rearranging Eq. (2.18), I obtain the following formula for the product's cumulative logarithmic return in integral form.

$$\begin{aligned}
\ln CLC_t - \ln CLC_0 = \lambda \left(\ln S_t - \ln S_0 \right) + \frac{\lambda - \lambda^2}{2} \sigma^2 t + (1-\lambda) \int_0^t \left(r_s + f_s^{SP} \right) ds \\
+ \lambda \int_0^t f_s^{SR} ds - f^I t.
\end{aligned} \tag{2.19}$$

This formula shows that the logarithmic return of CLCs over any investment horizon can be modeled as the logarithmic return of the underlying over the same period multiplied by the product's leverage factor, adjusted by a volatility term and other terms representing interest or issuer fees. As already highlighted in Section 2.2.3, volatility has a negative impact on the product's return irrespective of whether it is a long or short product, since for any λ larger than 1 or smaller than -1 the term $\frac{\lambda-\lambda^2}{2}$ is negative. It is also apparent from the formula that a larger interest rate r_s leads to a decreased (increased) return for long (short) certificates, while higher issuer fees generally decrease the return[13].

A discrete-time cumulative logarithmic return corresponding to (2.19) could be written as

$$\begin{aligned}\ln CLC_t - \ln CLC_0 \approx \lambda \left(\ln S_t - \ln S_0\right) + \frac{\lambda-\lambda^2}{2}\sigma^2 t + (1-\lambda)\Delta t \sum_{s=0}^{n-1}\left(r_s + f_s^{SP}\right) \\ + \lambda \Delta t \sum_{s=0}^{n-1} f_s^{SR} - f^I t, \qquad (2.20)\end{aligned}$$

where n corresponds to the length of the holding period in days. Δt is required to scale parameters to daily rates. The cumulative (non-logarithmic) return can be derived from Eq. (2.20) as follows.

$$\frac{CLC_t}{CLC_0} \approx \left(\frac{S_t}{S_0}\right)^{\lambda} \cdot \exp\left[\frac{\lambda-\lambda^2}{2}\sigma^2 t + (1-\lambda)\Delta t \sum_{s=0}^{n-1}\left(r_s + f_s^{SP}\right) + \lambda\Delta t \sum_{s=0}^{n-1} f_s^{SR} - f^I t\right]. \qquad (2.21)$$

Eq. (2.19) gives an exact relation between the return of a CLC and the return of its underlying. But since the products are not rebalanced continuously and the underlying might not be log-normally distributed, it is questionable whether the discretized version of the model in Eq. (2.20) and Eq. (2.21) is appropriate in practice. For this reason, its accuracy is tested in the following three subsections using different simulations and real-world data.

[13] Remind that f_s^{SP} is zero for short certificates and f_s^{SR} is zero for long certificates.

2.7.2 Simulation-based Model Validation with Constant Volatility

In the first simulation, I simulate daily returns of the underlying with a geometric Brownian motion and constant volatility. This simulation is in line with the assumptions of the theoretical model except that it takes account of the daily rebalancing frequency of CLCs. I use the historical mean and volatility of daily returns of the underlying assets from the issuance of the respective product to the end of the sample period for the parameters μ and σ of the geometric Brownian motion (see Eq. (2.12)).

The accuracy of the return model is tested for holding periods of 5, 20, 100 and 250 trading days. For each holding period and each product in the sample 100 simulation paths of the underlying asset and random values for the interest rate, financing spread, short rate and index fee out of a continuous uniform distribution are generated. The intervals of the uniform distributions have a width of multiple percentage points and are sufficiently large to ensure that the data has enough variability to test whether these terms are appropriately incorporated in the model.[14] Based on these simulation paths, the randomly drawn numbers for the interest rate, financing spread, short rate and index fee, and the pricing formula of CLCs, I calculate the products' cumulative logarithmic return $\ln CLC_t - \ln CLC_0$ for each simulation path. These returns are then used as dependent variable in the subsequent regression analyses.

I apply three regression models to test the theoretical return model. The first regression model basically corresponds to the return model as stated in Eq. (2.20) but with added regression coefficients. To check whether each variable of the model contributes to the cumulative return to the extent expected, a regression coefficient is assigned to each summand of the equation. The second regression model is similar. As in the first one, it includes a regression coefficient for the return of the underlying, but only one coefficient is assigned to the remainder of the equation, which is in the following referred to as "model intercept". I call it model intercept because if the return model in Eq. (2.20) is seen as a function of the cumulative logarithmic return of the underlying, it corresponds to the vertical intercept of the model in case of $\ln S_t - \ln S_0 = 0$.

[14] Another possibility would be the application of real numbers for the interest rate, financing spread, short rate and index fee. However, this option proved to be less convenient for the subsequent regression analysis due to low variability of the data.

Formally, the first two regression models are defined as

$$\ln CLC_t - \ln CLC_0 = \beta_0 + \beta_1\lambda\left(\ln S_t - \ln S_0\right) + \beta_2\frac{\lambda-\lambda^2}{2}\sigma^2 t + \beta_3(1-\lambda)\Delta t\sum_{s=0}^{n-1}\left(r_s\right) + \beta_4(1-\lambda)\Delta t\sum_{s=0}^{n}\left(f_s^{SP}\right) + \beta_5\lambda\Delta t\sum_{s}^{n}\left(f_s^{SR}\right) - \beta_6 f^I t + \epsilon, \tag{I}$$

$$\ln CLC_t - \ln CLC_0 = \beta_0 + \beta_1\lambda\left(\ln S_t - \ln S_0\right) + \beta_2 MI + \epsilon, \tag{II}$$

$$\text{with} \quad MI = \frac{\lambda-\lambda^2}{2}\sigma^2 t + (1-\lambda)\Delta t\sum_{s=0}^{n-1}\left(r_s + f_s^{SP}\right) + \lambda\Delta t\sum_{s=0}^{n-1} f_s^{SR} - f^I t.$$

β_0, β_1, ... are regression coefficients. MI corresponds to the model intercept if the regression coefficients are zero. The values used for the terms $\ln S_t - \ln S_0$, r_s, f_s^{SP}, f_s^{SR} and f^I correspond to the simulation output. σ^2 corresponds to the realized volatility of the simulation path of the underlying. Since the regression models (I) and (II) are equivalent to the theoretical model, β_0 would be equal to 0 and all other coefficients would be equal to 1 in case of a perfect fit.

The third regression model is an intercept-only model to measure the relative error of the theoretical model. The regressand is calculated as deviation between the effective product return and the product return predicted by the model in Eq. (2.20) divided by the effective product return. Formally, we have

$$\frac{\ln CLC_t - \ln CLC_0 - \left[\lambda\left(\ln S_t - \ln S_0\right) + MI\right]}{\ln CLC_t - \ln CLC_0} = \beta_0 + \epsilon. \tag{III}$$

The regression coefficient β_0 corresponds to the mean relative model error if the residuals are normally distributed. It indicates whether the model is accurate, i.e., whether it is overestimating ($\beta_0 < 0$) or underestimating ($\beta_0 > 0$) the effective return. The standard error of the coefficient, on the other hand, indicates whether the predictions of the model are precise. An accurate and precise model therefore implies that both the regression coefficient and its standard error are close to zero.

The results of the regression analysis are reported in Table 2.7.1. Judging by the (adjusted) R^2 measure, the model is very accurate in explaining short- and long-term returns of CLCs. Indeed, the regression coefficients are relatively close to the expected values, in particular for holding periods of 5 and 250 trading days. Some of the regression coefficients assigned to the financing spread, short rate or index fee range between 0.8 and 0.9 for holding periods of 20 and 100 trading days. Contrariwise, the volatility of the underlying seems to have a slightly larger

	$t=5$			$t=20$			$t=100$			$t=250$		
	(I)	(II)	(III)	(I)	(II)	(III)	(I)	(II)	(III)	(I)	(II)	(III)
Intercept	0.001***	0.002***	−0.01	0.01***	0.02***	0.01***	0.05***	0.07***	0.01*	0.04***	0.05***	0.02*
	(0.0002)	(0.0001)	(0.04)	(0.0005)	(0.0003)	(0.002)	(0.001)	(0.001)	(0.005)	(0.001)	(0.001)	(0.01)
$\lambda\left(\ln S_t - \ln S_0\right)$	1.02***	1.02***		1.02***	1.02***		1.01***	1.01***		1.01***	1.01***	
	(0.0004)	(0.0004)		(0.0005)	(0.0005)		(0.001)	(0.001)		(0.0002)	(0.0002)	
$\frac{\lambda-\lambda^2}{2}\sigma^2 t$	1.10***			1.21***			1.19***			1.07***		
	(0.002)			(0.002)			(0.001)			(0.0005)		
$(1-\lambda)\Delta t\sum_{s=0}^{n-1}\left(r_s\right)$	0.98***			1.02***			1.01***			1.02***		
	(0.03)			(0.02)			(0.01)			(0.002)		
$(1-\lambda)\Delta t\sum_{s=0}^{n-1}\left(f_s^{SP}\right)$	0.95***			0.88***			0.88***			0.98***		
	(0.02)			(0.01)			(0.01)			(0.002)		
$\lambda\Delta t\sum_{s=0}^{n-1}\left(f_s^{SR}\right)$	0.96***			0.83***			0.85***			0.98***		
	(0.02)			(0.01)			(0.01)			(0.002)		
$-f^I t$	0.99***			0.84***			0.98***			1.00***		
	(0.15)			(0.08)			(0.04)			(0.01)		
MI		1.09***			1.19***			1.16***			1.06***	
		(0.002)			(0.002)			(0.001)			(0.0004)	
Observations	33 892	33 892	33 892	33 882	33 882	33 882	33 824	33 824	33 824	33 802	33 802	33 802
R^2	0.99	0.99	0.00	0.99	0.99	0.00	0.99	0.99	0.00	1.00	1.00	0.00
Adjusted R^2	0.99	0.99	0.00	0.99	0.99	0.00	0.99	0.99	0.00	1.00	1.00	0.00

*p<0.1; **p<0.05; ***p<0.01

Table 2.7.1: Results of the simulation-based model validation with constant volatility. The dependent variable of the regression models (I) and (II) is the cumulative logarithmic return of CLCs and the dependent variable of the regression model (III) is the relative model error.

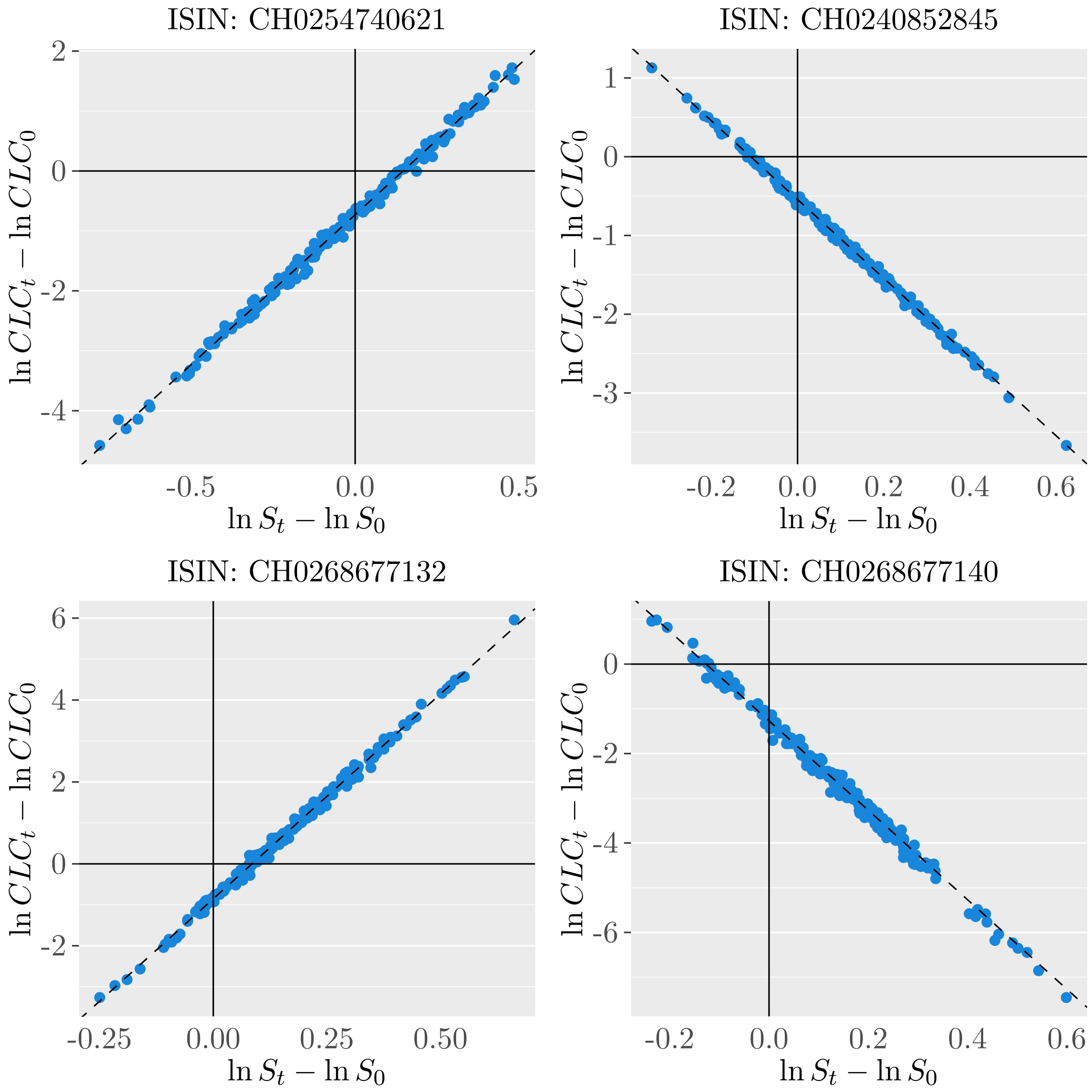


Figure 2.7.1: Simulation of the return of four randomly chosen CLCs over a holding period of one year. The vertical, dashed line represents the model in Eq. (2.20). The blue dots represent simulation outcomes.

impact on the product return than predicted. Apart from that, all values are roughly in line with the model, i.e., the intercept coefficient is between 0 and 0.07 and the other coefficients range between 0.9 and 1.02. The model error measured by regression model (III) ranges between -1% and 2%.

Figure 2.7.1 illustrates the accuracy of the model graphically. It shows the logarithmic return of four randomly chosen CLCs over one year as a function of the logarithmic return of the underlying over the same period based on the results of an independent but similar simulation. The only difference is that interest rates are kept constant to obtain a constant model intercept, which enables the display of the return model as a straight line. The blue dots represent simulation outcomes and, as anticipated in the model, suggest that there is a strong linear relationship between the logarithmic return of CLCs and the logarithmic return of their underlyings.

2.7.3 Simulation-based Model Validation with Time-varying Volatility

A property of the geometric Brownian motion is the log-normal distribution of stock returns. However, it is well-known that stock return distributions are leptokurtic and tend to have fat tails. To take account of this characteristic, a simulation with time-varying volatility is run using a GARCH(p, q) model with $p = q = 1$. The GARCH$(1, 1)$ model has proven to be a robust volatility model for equity instruments and to work effectively in forecasting (see, e.g., Andersen and Bollerslev, 1998; Hansen and Lunde, 2005). The model is specified as

$$\sigma_t^2 = \omega + \alpha\epsilon_{t-1}^2 + \beta\sigma_{t-1}^2, \tag{2.22}$$

$$\text{with} \quad \epsilon_{t-1} \sim \mathcal{N}\left(0, \sigma_{t-1}^2\right).$$

The initial value for the conditional variance σ_0^2 corresponds to the historical (long-term) variance during the investigation period σ^2. As in the precedent simulation, the innovations ϵ_t are used to calculate daily logarithmic returns of the underlying.

The simulation with time-varying volatility is performed once with predefined, fixed values for the parameters α and β (same values for all underlyings) and once with fitted values for each underlying using maximum likelihood estimation. The fixed parameters used in my study are 0.1 for α, 0.85 for β and $\sigma^2(1 - \alpha - \beta)$ for ω. These values are approximately in line with estimated parameters for equity indexes in the literature (see, e.g., Engle, 2001; Koopman et al., 2005; Sabbatini and Linton, 1998, which found values for α between 0.077 and 0.102 and values for β between 0.8 and 0.905). Except for the application of time-varying volatility, the simulations and regression models in this section are identical to the model validation approach with constant volatility.

The results of the regression analysis are given in Table 2.7.2 and Table 2.7.3. The simulation with fixed parameters leads to a slightly better goodness of fit. Otherwise, the results of both simulations are comparable to the results obtained with constant volatility. The beta assigned to the volatility term is again slightly above 1, ranging between 1.13 and 1.26. The beta assigned

	t = 5			t = 20			t = 100			t = 250		
	(I)	(II)	(III)	(I)	(II)	(III)	(I)	(II)	(III)	(I)	(II)	(III)
Intercept	0.002^{***}	0.003^{***}	-0.05	0.01^{***}	0.02^{***}	0.02^{*}	0.03^{***}	0.04^{***}	-0.01	0.07^{***}	0.10^{***}	0.01
	(0.0003)	(0.0002)	(0.07)	(0.001)	(0.0003)	(0.01)	(0.001)	(0.0005)	(0.02)	(0.002)	(0.001)	(0.004)
$\lambda\left(\ln S_t - \ln S_0\right)$	1.02^{***}	1.02^{***}		1.02^{***}	1.02^{***}		1.01^{***}	1.01^{***}		1.01^{***}	1.01^{***}	
	(0.001)	(0.001)		(0.001)	(0.001)		(0.0003)	(0.0003)		(0.0004)	(0.0004)	
$\frac{\lambda-\lambda^2}{2}\sigma^2 t$	1.17^{***}			1.26^{***}			1.13^{***}			1.13^{***}		
	(0.003)			(0.002)			(0.001)			(0.001)		
$(1-\lambda)\Delta t\sum_{s=0}^{n-1}\left(r_s\right)$	1.04^{***}			1.01^{***}			1.01^{***}			1.01^{***}		
	(0.05)			(0.02)			(0.01)			(0.004)		
$(1-\lambda)\Delta t\sum_{s=0}^{n-1}\left(f_s^{SP}\right)$	0.93^{***}			0.86^{***}			0.94^{***}			0.94^{***}		
	(0.04)			(0.02)			(0.004)			(0.004)		
$\lambda\Delta t\sum_{s=0}^{n-1}\left(f_s^{SR}\right)$	0.88^{***}			0.75^{***}			0.93^{***}			0.95^{***}		
	(0.04)			(0.02)			(0.004)			(0.004)		
$-f^I t$	1.22^{***}			0.80^{***}			0.99^{***}			1.02^{***}		
	(0.25)			(0.11)			(0.03)			(0.02)		
MI		1.16^{***}			1.23^{***}			1.11^{***}			1.10^{***}	
		(0.003)			(0.002)			(0.001)			(0.001)	
Observations	33 894	33 894	33 894	33 883	33 883	33 883	33 820	33 820	33 820	33 800	33 800	33 800
R^2	0.99	0.99	0.00	0.99	0.99	0.00	1.00	1.00	0.00	1.00	1.00	0.00
Adjusted R^2	0.99	0.99	0.00	0.99	0.99	0.00	1.00	1.00	0.00	1.00	1.00	0.00

*p<0.1; **p<0.05; ***p<0.01

Table 2.7.2: Results of the simulation-based model validation with time-varying volatility and predefined GARCH parameters. The dependent variable of the regression models (I) and (II) is the cumulative logarithmic return of CLCs and the dependent variable of the regression model (III) is the relative model error.

	$t=5$			$t=20$			$t=100$			$t=250$		
	(I)	(II)	(III)	(I)	(II)	(III)	(I)	(II)	(III)	(I)	(II)	(III)
Intercept	0.002***	0.003***	−0.06	0.01***	0.02***	−0.002	0.05***	0.07***	0.02*	0.08***	0.11***	0.07*
	(0.001)	(0.0002)	(0.05)	(0.001)	(0.0004)	(0.01)	(0.001)	(0.001)	(0.01)	(0.002)	(0.001)	(0.04)
$\lambda\left(\ln S_t - \ln S_0\right)$	1.04***	1.04***		1.04***	1.04***		1.02***	1.02***		1.02***	1.02***	
	(0.001)	(0.001)		(0.001)	(0.001)		(0.001)	(0.001)		(0.0005)	(0.0005)	
$\frac{\lambda-\lambda^2}{2}\sigma^2 t$	1.18***			1.19***			1.19***			1.13***		
	(0.004)			(0.002)			(0.001)			(0.001)		
$(1-\lambda)\Delta t\sum_{s=0}^{n-1}\left(r_s\right)$	1.20***			1.02***			0.99***			1.02***		
	(0.08)			(0.03)			(0.01)			(0.01)		
$(1-\lambda)\Delta t\sum_{s=0}^{n-1}\left(f_s^{SP}\right)$	1.03***			0.98***			0.94***			1.00***		
	(0.06)			(0.03)			(0.01)			(0.005)		
$\lambda\Delta t\sum_{s=0}^{n-1}\left(f_s^{SR}\right)$	1.00***			0.86***			0.86***			0.94***		
	(0.06)			(0.02)			(0.01)			(0.005)		
$-f^I t$	0.92**			1.05***			0.97***			1.01***		
	(0.38)			(0.16)			(0.05)			(0.03)		
MI		1.18***			1.19***			1.17***			1.11***	
		(0.004)			(0.002)			(0.001)			(0.001)	
Observations	33 800	33 800	33 800	33 741	33 741	33 741	33 570	33 570	33 570	33 451	33 451	33 451
R^2	0.97	0.97	0.00	0.98	0.98	0.00	0.99	0.99	0.00	1.00	1.00	0.00
Adjusted R^2	0.97	0.97	0.00	0.98	0.98	0.00	0.99	0.99	0.00	1.00	1.00	0.00

$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Table 2.7.3: Results of the simulation-based model validation with time-varying volatility and fitted GARCH parameters. The dependent variable of the regression models (I) and (II) is the cumulative logarithmic return of CLCs and the dependent variable of the regression model (III) is the relative model error.

to the return of the underlying is relatively stable with values between 1.01 and 1.04. The other regression coefficients are between 0.75 and 1.22. The simulation with fixed parameters results in roughly the same model accuracy as the simulation with constant volatility. However, the model accuracy for the simulation with fitted parameters is lower than before, with a mean model error ranging between -6% and 7%. Possibly, the estimation window for fitting the parameters, which corresponds to the investigation period of five years, is too short to obtain realistic estimates. Consequently, the return distributions of the underlyings resulting from the short estimation window might have unrealistic shapes and differ greatly from the log-normal distribution, which could explain the slightly worse results for the simulation with fitted parameters.

2.7.4 Model Validation with Empirical Data

The last model validation is performed with empirical data, where the products' returns predicted by the theoretical model are compared to effective returns. The results are displayed in Table 2.7.4. As the (adjusted) R^2 measure shows, the goodness of fit is not worse than previously obtained values with simulated returns. Moreover, the regression coefficient assigned to the volatility term ranges between 0.9 and 1.05 and is therefore much closer to 1. The regression coefficient assigned to the return of the underlying is in line with previously obtained results and ranges between 1.02 and 1.03.

In contrast, the regression coefficients assigned to the interest rate, financing spread, short rate and index fee deviate from 1, in some cases even drastically. It seems that the lack of variability of these variables is a serious shortcoming. For instance, the index fee amounts to 0.7% for 223 products, 1% for 112 products and 1.5% for 4 products, which makes it difficult to capture its impact on the return correctly. However, it should be added that the variables with low variability have a relatively small effect size. This becomes apparent when comparing the beta coefficient of the model intercept from model (II) to the beta coefficient assigned to the volatility term in model (I). These are in general very close, which suggests that the overall predictive capability is not affected by the lack of data variability. It appears to be difficult to prove the correct incorporation of all variables and parameters in the model based on empirical data. But given the results obtained by the – in this regard probably more meaningful – simulation-based validation, I believe that the theoretical model reflects real-world data well.

The average model error ranges from -1% to 7%, with the exception of the value obtained

	$t=5$			$t=20$			$t=100$			$t=250$		
	(I)	(II)	(III)	(I)	(II)	(III)	(I)	(II)	(III)	(I)	(II)	(III)
Intercept	0.001	-0.002^{***}	0.004	0.001	-0.002^{***}	0.27	-0.01	-0.004^{**}	0.003	-0.06^{**}	-0.01^{***}	0.07
	(0.001)	(0.0001)	(0.01)	(0.002)	(0.0003)	(0.21)	(0.01)	(0.002)	(0.004)	(0.03)	(0.005)	(0.05)
$\lambda\,(\ln S_t - \ln S_0)$	1.03^{***}	1.03^{***}		1.03^{***}	1.03^{***}		1.03^{***}	1.03^{***}		1.02^{***}	1.02^{***}	
	(0.0004)	(0.0004)		(0.001)	(0.001)		(0.001)	(0.001)		(0.002)	(0.002)	
$\frac{\lambda-\lambda^2}{2}\sigma^2 t$	0.90^{***}			1.00^{***}			1.04^{***}			1.05^{***}		
	(0.002)			(0.002)			(0.003)			(0.004)		
$(1-\lambda)\Delta t\sum_{s=0}^{n-1}(r_s)$	1.25^{***}			1.22^{***}			1.17^{***}			1.13^{***}		
	(0.11)			(0.10)			(0.10)			(0.14)		
$(1-\lambda)\Delta t\sum_{s=0}^{n-1}\left(f_s^{SP}\right)$	3.32^{***}			2.33^{***}			1.50^{***}			1.20^{***}		
	(0.27)			(0.23)			(0.24)			(0.31)		
$\lambda\Delta t\sum_{s=0}^{n-1}\left(f_s^{SR}\right)$	2.27^{***}			1.02^{***}			0.03			-0.09		
	(0.08)			(0.08)			(0.09)			(0.10)		
$-f^I t$	13.61^{***}			4.53^{*}			-3.38			-6.47^{**}		
	(2.70)			(2.33)			(2.35)			(2.89)		
MI		0.90^{***}			1.00^{***}			1.02^{***}			1.02^{***}	
		(0.002)			(0.002)			(0.003)			(0.004)	
Observations	54 906	54 906	54 906	13 610	13 610	13 610	2 597	2 597	2 597	891	891	891
R^2	0.99	0.99	0.00	1.00	1.00	0.00	1.00	1.00	0.00	1.00	1.00	0.00
Adjusted R^2	0.99	0.99	0.00	1.00	1.00	0.00	1.00	1.00	0.00	1.00	1.00	0.00

$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Table 2.7.4: Results of the model validation with empirical data. The dependent variable of the regression models (I) and (II) is the cumulative logarithmic return of CLCs and the dependent variable of the regression model (III) is the relative model error.

for a holding period of 20 days, which surprisingly amounts to 27%. This value, however, comes along with a relatively large standard deviation. Accordingly, it is not significantly different from 0, which also applies to average model errors obtained for the other holding periods.

Overall, I conclude that the cumulative logarithmic return of CLCs can be explained well by the leveraged cumulative logarithmic return of the underlying, a volatility adjustment term and a fee and interest reduction. This applies to a broad range of processes for the underlying and to empirical data. The estimated regression coefficients assigned to the volatility term (β_2) is, however, mostly larger than 1, which implies that the volatility of the underlying has a stronger effect on the return of CLCs than predicted by the model.

A possible explanation for this is that the model generally tends to predict values that are too high, which then results in a larger regression coefficient for the volatility term to reduce the model output.[15] One can show numerically that the model output is relatively large compared to the effective cumulative product return if the latter is negative (especially if it is only slightly negative). This explanation is therefore plausible if the cumulative product return is negative on average or – because least squares regressions are dragged towards outliers – if a small minority of simulation paths produces extremely large model errors. In any case, the relatively large regression coefficient for the volatility term can be found in all simulation approaches and thus irrespective of whether returns of the underlying are log-normally distributed or not. I thus believe that the assumption on the rebalancing frequency is more critical for the model accuracy.

2.8 Return Distribution

The model introduced in the last section allows for an analysis of the return distribution for varying holding periods and leverage factors. Building on the same framework, I derive the return probability density of CLCs as a function of the leverage factor and the holding period. The resulting distributions are then compared to historical returns.

[15]Note that the volatility term ($\frac{\lambda-\lambda^2}{2}\sigma^2 dt$) is always negative.

2.8.1 Theoretical Return Distribution

For simplicity, I assume constant interest and issuer fees in the subsequent analysis. In that case, according to Eq. (2.17), the logarithmic return over the investment period $[0, t]$ equals

$$\ln \frac{CLC_t}{CLC_0} = \left[\lambda\mu + (1-\lambda)\left(r + f^{SP}\right) + \lambda f^{SR} - f^I - \frac{1}{2}\lambda^2\sigma^2\right] t + \lambda\sigma W_t. \tag{2.23}$$

Since W_t is the only stochastic component and normally distributed with $W_t \sim \mathcal{N}(0, t)$, it follows that

$$\ln \frac{CLC_t}{CLC_0} \sim \mathcal{N}\left(\hat{\mu}, \hat{\sigma}^2\right) \quad \text{or} \quad \frac{CLC_t}{CLC_0} \sim \mathcal{LN}\left(\hat{\mu}, \hat{\sigma}^2\right), \tag{2.24}$$

$$\text{with} \quad \hat{\mu} = \left[\lambda\mu + (1-\lambda)\left(r + f^{SP}\right) + \lambda f^{SR} - f^I - \frac{1}{2}\lambda^2\sigma^2\right] t$$

$$\text{and} \quad \hat{\sigma}^2 = \lambda^2\sigma^2 t.$$

The probability density function is thus given by

$$f\left(\frac{p_t}{p_0}\right) = \frac{1}{\sqrt{2\pi}\hat{\sigma}\frac{CLC_t}{CLC_0}} \cdot \exp\left[-\frac{\left(\ln\frac{CLC_t}{CLC_0} - \hat{\mu}\right)^2}{2\hat{\sigma}^2}\right]. \tag{2.25}$$

Figure 2.8.1 shows probability density functions for varying leverage factors and over holding periods of 1, 7, 30, 90 and 365 days. All parameters correspond to average values during the investigation period. To facilitate the comparison between different investment horizons, the density functions are only displayed in the range of -1 to 2 (ordinary return) and -2 to 2 (logarithmic return). However, that does not affect the overall interpretation of the diagrams.

There are two peculiarities that are particularly apparent when analyzing the distributions. First, short certificates have a much lower performance than long certificates, which is in line with the overall positive long-term trend of stock prices. For instance, when comparing the mean logarithmic returns of pairs of long and short certificates, a clear difference can be observed. The difference becomes increasingly obvious with longer holding periods.

Second, there is an increasing skewness of the distribution of ordinary returns over long-term investment horizons. The distribution is relatively symmetrical for a holding period of 1 day but gets an increasingly long tail on the right for holding periods of 7 days or more, in particular if the leverage factor is extremely negative or extremely positive. The skewness of the distribution of CLCs with leverage factors -10 and 10 over an investment period of 365 days is so large that

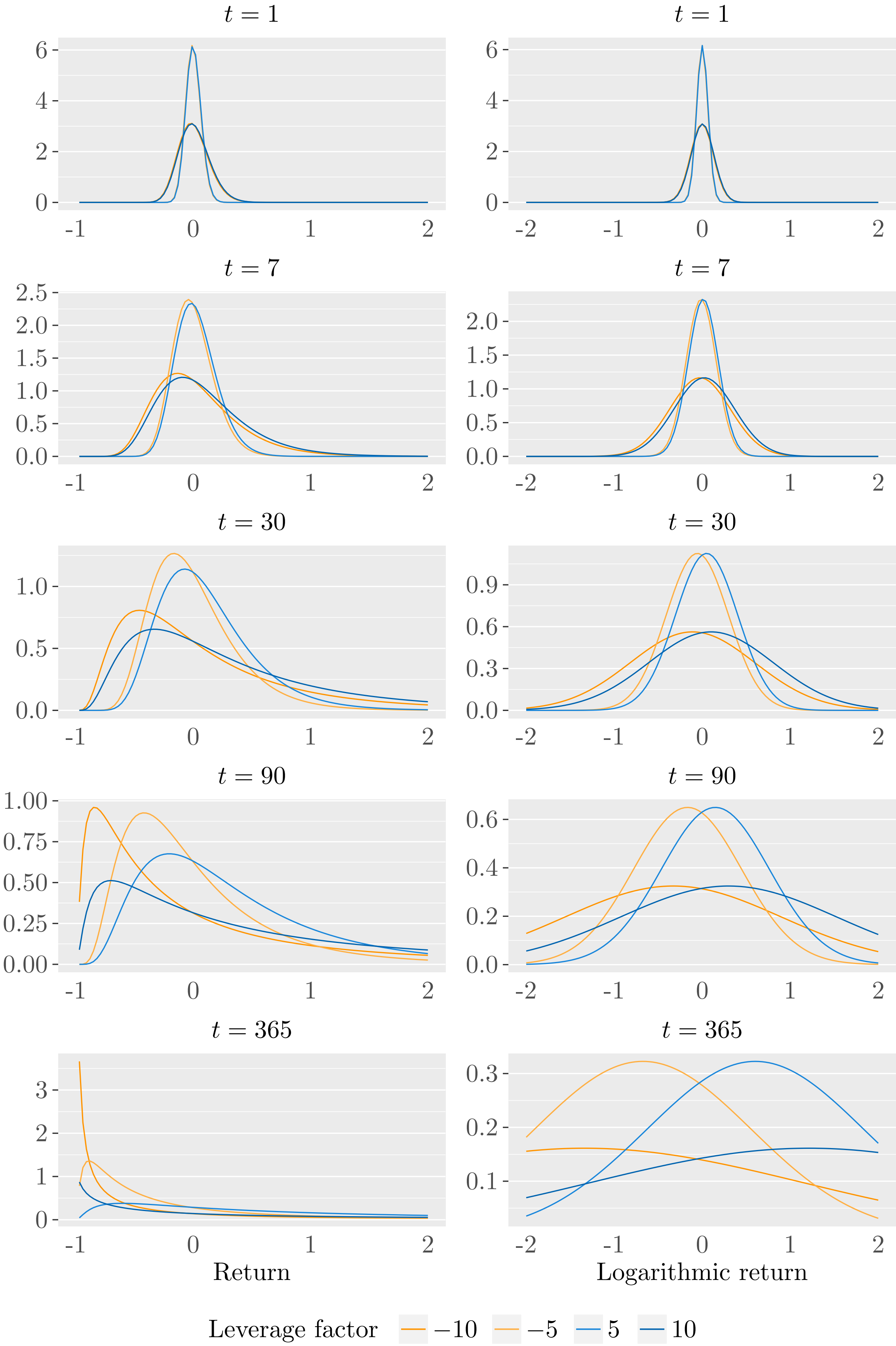


Figure 2.8.1: Probability density functions of ordinary (left) and logarithmic (right) returns of CLCs based on the theoretical model for different holding periods and leverage factors. t corresponds to the holding period in days.

the left tail is no longer visible.

Interestingly, for $\lambda \to \infty$ as well as for $t \to \infty$ the loss probability given by

$$P\left(\frac{CLC_t}{CLC_0} \leq 1\right) = \Phi\left(\frac{-\hat{\mu}}{\hat{\sigma}}\right) = \Phi\left[\frac{-\left(\mu + \left(\frac{1}{\lambda} - 1\right)\left(r + f^{SP}\right) + f^{SR} - \frac{1}{\lambda}f^I - \frac{1}{2}\lambda\sigma^2\right)\sqrt{t}}{\sigma}\right], \tag{2.26}$$

with $\Phi(\cdot)$ being the cumulative standard normal distribution, tends to 100%, since the term within the squared brackets in Eq. (2.26) is dominated mainly by the variance of the underlying. At the same time, the mean return given by

$$\mathbf{E}\left(\frac{CLC_t}{CLC_0}\right) = \exp\left(\hat{\mu} + \frac{1}{2}\hat{\sigma}^2\right) = \exp\left[\left(\lambda\mu + (1-\lambda)\left(r + f^{SP}\right) + \lambda f^{SR} - f^I\right)t\right] \tag{2.27}$$

tends to infinity. Hence, an investment in a long CLC with extremely large leverage and/or with an extremely long holding period has similar risk-return characteristics as the well-known St. Petersburg lottery. For short CLCs with $\lambda \to -\infty$ the loss probability tends to 100% as well, however, the expected return converges towards a total loss. These findings also show why a lot of these products have strongly negative returns.

2.8.2 Historical Return Distribution

Figure 2.8.2 shows histograms of ordinary and logarithmic historical returns of CLCs. For better comparison, the same holding periods are analyzed as in the previous section.

In general, the histograms of historical returns have a similar shape as the theoretical distributions. Logarithmic returns are relatively symmetrically distributed, while there is a clearly recognizable positive skewness of ordinary returns over long-term investment periods. However, the theoretical distributions seem to have a more pronounced skewness, especially for products with leverage factors -10 and 10. The long tail on the right of the historical distribution is clearly recognizable only for holding periods of 90 days or more. These findings are in line with Lu et al. (2009), who showed that compounding only affects the return for investments longer than one month.

The deviation between the theoretical and historical distributions might be explained by the fact that 80% of the products from the sample have a leverage factor between -6 and 6. As a result, the historical distributions rather look like the theoretical distributions for the leverage

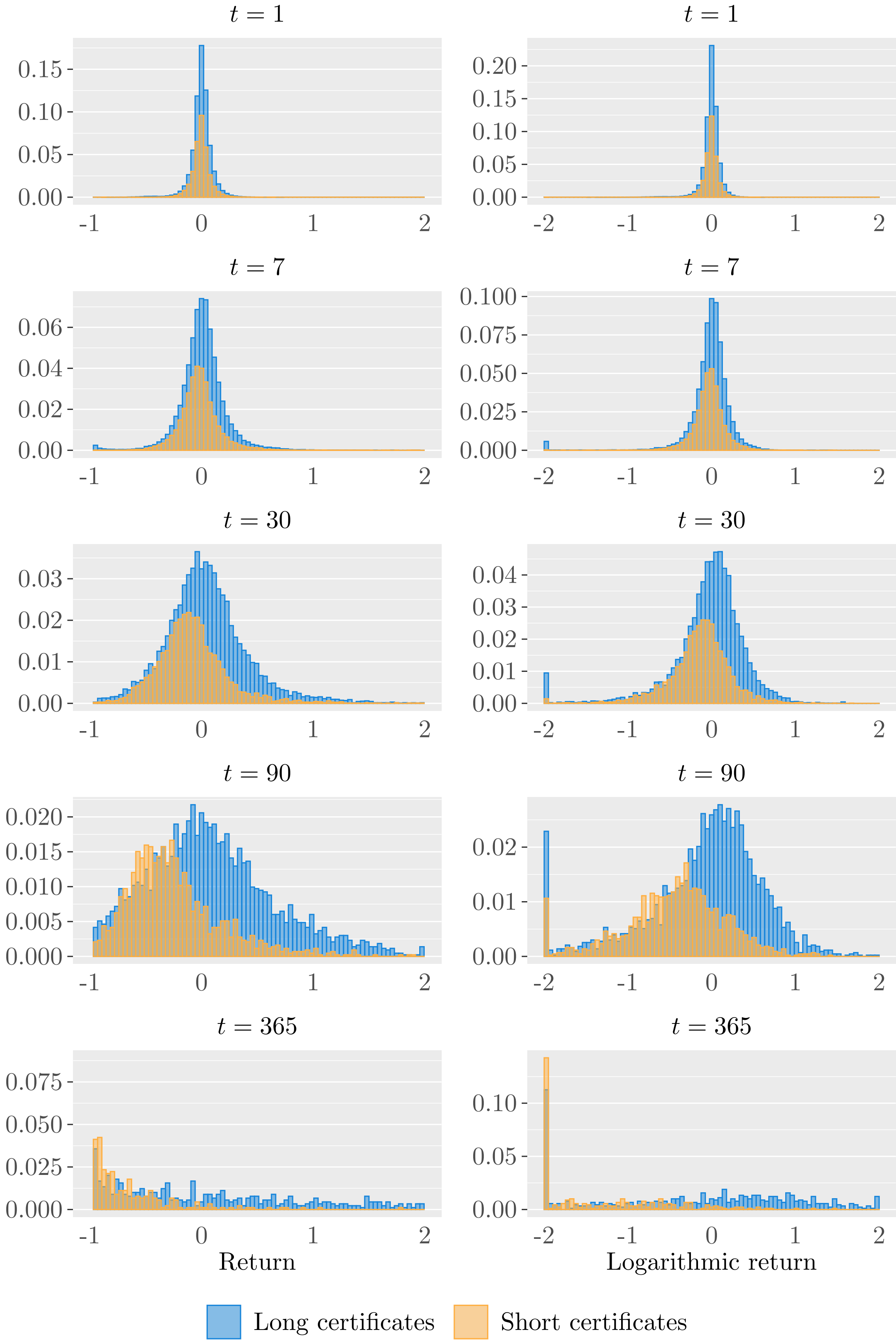


Figure 2.8.2: Histograms of ordinary (left) and logarithmic (right) returns of CLCs for different holding periods. t corresponds to the holding period including non-trading days. Returns outside of the scale limits are included in the boundary bars.

factors -5 and 5. Unfortunately, the amount of data does not allow for an isolated analysis of CLCs with different leverage factors.

Another possible driver for the greater skewness of the theoretical distributions could be the mismatched rebalancing frequency. In contrast to the continuous rebalancing frequency assumed in the model, CLCs are rebalanced only once a day in practice. This explanation is supported by Trainor (2011), who studied the difference between daily and monthly rebalancing LETFs and found that the compounding effect is more pronounced with increasing rebalancing frequency.

The historical distributions also reveal that there are more extreme negative logarithmic returns than extreme positive ones for long-term investment horizons. This observation is in line with theoretical distributions for short certificates. But in contrast to the theoretical analysis, historical logarithmic returns of long certificates also seem to have a heavier tail on the left. However, the distribution of long-term returns is much less smooth due to the smaller amount of available data, which makes a conclusive argument based on empirical data difficult.

2.9 Conclusion

CLCs are relatively new financial products, which enable a leveraged participation in the underlying asset for risk-seeking investors. The main innovation of these certificates is the constant leverage on a daily basis, i.e., their daily return (roughly) corresponds to the daily return of the underlying multiplied by the product's leverage factor. The increasing popularity of CLCs might be attributed to their seemingly easy comprehensibility associated with this product feature. However, many investors may not be familiar with the implications of the daily rebalancing on the long-term return. Already a brief look at a few price paths of CLCs over a longer period of time suggests that their return prospects may not be as good as it initially seems. Many of these products have a negative return over an investment period of one year despite a positive development of the underlying. A substantial part of the products suffers a price decline that is practically a total loss.

I examine this phenomenon in my study with a profound theoretical and empirical analysis of the short- and long-term return of these certificates based on the price-setting formula communicated in term sheets. The analysis starts with a comparison of the return of CLCs with the leveraged return of the underlying over holding periods longer than one day. I often find a large but insignificant deviation between these two returns, as the variance of the deviation is also relatively large. The deviation is mainly related to the effect of compounding, which can have a positive or negative impact on the products' return. In general, compounding has positive (negative) effects in periods of low (high) volatility. Due to the low interest level with partly negative rates during the investigation period, interest does not significantly lower or increase the return despite the large debt or deposit portion in some CLCs. Issuer fees, however, negatively affect the products' return, especially in case of a favorable product performance. They contribute to a return decrease of 3.2% on average over a holding period of one year. However, neither the return decrease due to issuer fees nor the analysis of the total return deviation can answer the question of why a majority of the products results in a large loss in the long run.

I thus further deepen my analysis by presenting a model that links the (long-term) return of CLCs to the return of its underlying. It shows that the products' logarithmic return is best predicted by the logarithmic return of the underlying multiplied by the leverage factor minus a deduction related to the volatility of the underlying, interest and issuer fees. A regression analysis with simulated and empirical returns for the underlying showed that the model has a high goodness of fit also in case of time-varying volatility. The relative model error mostly amounts to maximally a few percentage points and has a low standard deviation, which indicates that the model predictions are accurate as well as precise.

Based on the model, I derive a theoretical return distribution and study the effects of different holding periods and leverage factors on its shape. The findings show that the length of the holding period and the size of the leverage factor have a negative impact on the average product return for short certificates but not for long certificates. These two factors, however, also lead to a positively skewed return distribution with long tails on the right. Therefore, (long) certificates held over long investment periods are associated with an increasing loss probability (despite higher expected returns), which finally explains the large amount of failed products. The right-skewed shape of the return distribution can also be found in empirical product returns.

A limitation of this study is its exclusive focus on products with equities and indexes as underlying. Other asset classes, such as futures, commodities, currencies or interest rates, might have a differently shaped return distribution. My results suggest that the process for the underlying is not crucial for the model accuracy. Nonetheless, a profound analysis of the implications of different return distributions on the long-term performance of the products in general or the compounding effect in particular would be required to answer this question conclusively.

In any case, and despite the criticism of investment products with constant leverage for not being suited as long-term investments in many scholarly articles (see, e.g., Lu et al., 2009; Murphy and Wright, 2010; Charupat and Miu, 2011; Tang and Xu, 2013), I argue that investors – or rather speculators – looking for lottery-like risk-return characteristics, where a high profit potential comes along with a high loss probability, should consider CLCs as an alternative to other leveraged instruments.

Chapter 3

BEHAVIORAL ASPECTS OF STRUCTURED PRODUCT INVESTMENTS

Many economic models are based on rationally acting market participants. The efficient market hypothesis, for instance, suggests that asset prices fully reflect all relevant information (Fama, 1970). Thus, assets always trade at their fair value, which makes it impossible to profit from arbitrage gains. However, multiple studies report different "anomalies" that indicate that the efficient market hypothesis might not hold at least in its most puristic form. These anomalies cannot be captured in a framework with rational, wealth-maximizing market participants.

That is where behavioral finance can be applied. It combines psychology with financial theory by explaining how cognitive activity effects the financial environment and provides a theoretical background for biases in human decision-making. These biases – or psychological deficiencies – might have their meaning in nature. However, they might lead to irrational investment decisions. Understanding the mental imperfection is of crucial importance for investors, analysts, brokers, portfolio managers, traders and financial executives, not to find a way of "beating the market", i.e., gaining abnormal returns, but to be more aware of their mental shortcomings and to take decisions that better reflect their own or their principal's preferences.

The role of behavioral decision making when it comes to investments in structured products is particularly interesting due to the complexity of the payoff structure and the relatively inconvenient probability distributions. Prior literature has shown that the demand for these products is not only driven by rational reasons (see Section 3.1.4). In this thesis, two research studies are presented that build on this literature by illustrating the impact of certain behavioral biases on structured product investment experimentally and by providing insights that can result in concrete guidance for investors, issuers and regulators to improve investment decisions.

The next sections contain a literature review with publications on financial decision making and the role of behavioral biases in investment decisions with a particular emphasis on theories and biases relevant for structured product investments. I also give a methodological background for experiments in finance before introducing the own research studies.

3.1 Financial Decision Making and Cognitive Biases in Investment Decisions

3.1.1 Prospect Theory

One of the most common and seminal concepts in financial decision making is the prospect theory of Kahneman and Tversky (1979). It provides a descriptive model of decisions under risk. It assumes that decision makers have a reference point (e.g., current wealth), and deviations from this reference point rather than absolute outcomes are crucial for their decisions. Based on the reference point, outcomes of a risky lottery are classified as profit or loss. According to prospect theory, decision makers are risk-averse over profits, which implies that they prefer guaranteed gains over uncertain gambles. Contrariwise, people are risk-seeking over losses and prefer to risk an uncertain and high loss over a certain but smaller loss. Also, they favor avoiding losses rather than gaining profits of the same amount, which is referred to as loss aversion. Based on these preferences, a so-called value function can be derived (see Figure 3.1.1), where a value (or utility) is assigned to each potential outcome. In contrast to expected utility theory, the value function is not linear but concave for profits (risk aversion), convex for losses (risk proclivity) and generally steeper for losses than for profits (loss aversion).

In addition, prospect theory states that probability changes can have different psychological effects depending on the probability level. For example, a change from 0% to 1% or from 99% to 100% is perceived as more important than one from 50% to 51%. Accordingly, a decision weight is assigned to each probability level, which results in the so-called probability weighting function (see Figure 3.1.1). The function shows that probabilities slightly larger than 0% have a disproportionately high decision weight, whereas probabilities slightly smaller than 100% have a disproportionately low decision weight. This psychological effect resulting from the probability reduction from certain to probable is also referred to as certainty effect (see Tversky and Kahneman, 1986).

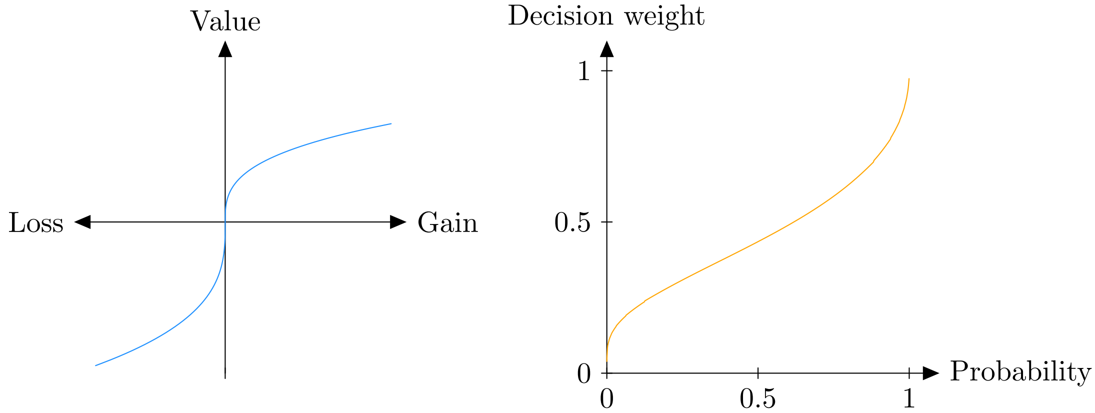


Figure 3.1.1: Prospect theory's value function (left) and probability weighting function (right) of a typical decision maker (see Kahneman and Tversky, 1979)

The combination of the value and probability weighting functions provides a theoretical basis for the explanation of different behavioral biases. Next to loss aversion and the certainty effect, there are many other examples of irrational behavior that can be modeled within or explained by prospect theory.

The Allais paradox, for instance, indicates that the addition of equal outcomes to each of the choice options in a lottery might have an effect on the preferences between the different choice options (see Allais, 1953). In a choice problem where decision makers can choose between a gain of 2 400 with certainty and a lottery where they can gain 2 500 with a probability of 33%, 2 400 with a probability of 66% and 0 with a probability of 1%, people typically choose the certain gain. However, in a choice problem where people can choose between a lottery where they can gain 2 400 with a probability of 34% and 0 with a probability of 66% and another lottery where they can gain 2 500 with a probability of 33% and 0 with a probability of 67%, they typically choose the second lottery. This is insofar remarkable as the second choice problem is obtained by removing a 66% chance of winning 2 400 from both choice options. The decisions of typical decision makers are thus a violation of the independence axiom of expected utility theory. However, this behavior can be explained by the disproportionately high weighting of the 1% probability of not gaining anything in the first choice problem (see Kahneman and Tversky, 1979).

The framing effect occurs when different ways of presenting something result in different decisions.[1] In prospect theory, outcomes are framed either as profit or loss depending on the decision maker's reference point. A different presentation can shift the reference point and thus effectuate a different decision (see Tversky and Kahneman, 1981). The framing effect can also affect the outcome of the subsequent studies and is considered in the experimental design (see Section 3.3.4 and Section 3.4.4).

The disposition effect explains how investors tend to sell assets after a price increase and keep assets after a price decrease even though it is often a poor-performing strategy. If the asset price at the time of investment is the investor's reference point, then a price increase (decrease) is perceived as profit (loss) and thus coincides with risk averse (risk seeking) behavior, which induces investors to sell (keep) the asset (see Shefrin and Statman, 1985).

The endowment effect describes people's relatively high willingness to pay for retaining something they own compared to obtaining something they do not own. This effect can be seen as a result of the relatively high drop in value for losses as compared to the increase in value for profits in prospect theory's value function (see Kahneman et al., 1991).

The status quo bias stands for an excessive preference of the current state. It can be partly explained by prospect theory. When considering the status quo as reference point, switching from the status quo is associated with a gain or a loss. Since people prefer avoiding losses rather than gaining profits, they are biased in favor of the status quo (see Samuelson and Zeckhauser, 1988).

3.1.2 Salience Theory

As an alternative to prospect theory, Bordalo et al. (2012) created another decision making model, which they call salience theory. Salience refers to the inappropriate weighting of one object compared to another due to differently directed attention. Similar to prospect theory, it incorporates the assumption of subjective probability weighting different from objective probabilities. However, in salience theory these weights depend not only on the probability level but also on the salience of the respective lottery outcome. Salience is modeled as the (modulus of the) relative deviation from the average. Mostly, salience theory and prospect theory arrive

[1] In Tversky and Kahneman's (1981) study for instance participants could choose between two treatments for 600 people with a deadly disease. The first treatment results in 200 survivals and 400 deaths and the second treatment saves all with a probability of $\frac{1}{3}$ and no one with a probability of $\frac{2}{3}$, respectively. The choice problem was "framed" either in a positive way, i.e., in terms of how many people will survive, or in a negative way, i.e., in terms of how many people will die. The first treatment was chosen mostly by participants with positive framing and the second treatment was chosen mostly by participants with negative framing.

at similar results. However, for instance when small probabilities are not coupled with salient payoffs, these two theories can draw different conclusions.

The enhancement of salience theory lies in the ability to consider the context. It allows to incorporate further behavioral biases like the less-is-better effect, which occurs when low-value options are valued more than high-value options[2] (see Hsee, 1998), the ratio bias, which occurs when preferences change after expanding the scale of an attribute[3] (see Burson et al., 2009) or other so-called preference reversals (Bordalo et al., 2012).

3.1.3 Other Cognitive Biases

In addition to the above-named mental shortcomings modeled within the prospect theory and salience theory, there are still a lot more cognitive biases that affect human decision-making. The biases that are considered to be the most relevant when it comes to investment decisions are described below.

Overconfidence occurs when people rate themselves above-average when evaluating desirable properties. Overconfidence can lead to excessive trading, which on average results in a worse performance and a lower expected utility for traders or their principals (see Odean, 1998).

The familiarity heuristic is applied when familiar places, products and people are preferred over unknown (see Park and Lessig, 1981). It might be one of the reasons for the home bias, i.e., the general trend of investing in domestic assets (see French and Poterba, 1991).

The confirmation bias stands for a specific form of selective perception where only information that coincides with own beliefs is considered, which can make investors persist on their strategy even if it is poor-performing (see Nickerson, 1998).

The representativeness heuristic or bias makes people overweight the representative characteristics of an object, defined as the characteristics that occur relatively more frequently than in a reference object. The bias can cause negative implications due to probability misestimation, e.g., when investing in a hedge fund because of its outstanding performance in the past (see

[2]E.g., people are willing to pay more for an overfilled ice cream cup with 7 oz of ice cream than for an underfilled cup with 8 oz of ice cream if evaluated independently from each other.

[3]E.g., people prefer to subscribe for a movie-rental plan with 7 new movies per week for USD 10 per month over a plan with 9 new movies per week for USD 12 per month. However, when expanding the scale to 364 and 468 movies per year (number of movies per week multiplied by 52), the second plan for USD 12 per month is preferred.

Kahneman and Tversky, 1972). It is also responsible for the so-called gambler's fallacy[4], the regression fallacy[5] and the conjunction fallacy[6].

The anchoring effect stands for judgment based on an arbitrary "anchor". For example, after receiving a random number from 0 to 100 (= anchor), the subjects of Tversky and Kahneman's (1974) study were asked first to assess whether the percentage of African UN member states is above or below the random number and secondly to give an exact estimate of the percentage. The anchor significantly influenced the estimated values.

There is empirical evidence that stocks with low returns over a given period tend to have high returns in the subsequent period and vice versa (Bondt and Thaler, 1985). This phenomenon is attributed to overreaction in the market: Market participants that are faced with new information start to trade the affected stocks excessively and, as a result, create an overly large short-term effect on stock prices, which disappears later on. Possible behavioral causes of overreaction are herding, the availability bias and myopia. Herding behavior is the tendency to imitate the actions or beliefs of large groups, be it because of social pressure or the rationale that large groups cannot be wrong. It can have major implications for financial markets leading to bubbles and crashes (see Hirshleifer and Hong Teoh, 2003). The availability bias occurs when people overestimate probabilities of events if they are easier to remember, e.g., when they occurred recently (see Tversky and Kahneman, 1973). Finally, myopia induces people to take a short-term view. Consequently, they react more to recent information, especially to recent downward movements of stock prices. Due to this close connection to loss aversion, the two biases are often combined in the cumulative term "myopic loss aversion" (see Benartzi and Thaler, 1995).[7]

[4] The gambler's fallacy is understood as the belief that a random event becomes more likely if it has not occurred for a long time, or more unlikely if it occurred recently. It is especially associated with gamblers (see Kahneman and Tversky, 1972).

[5] The regression fallacy is defined as the belief in causal effectiveness of actions after natural fluctuations, e.g., when punishing a student after exceptionally poor grades is followed by normal grades (see Gilovich, 2008, p. 23–28).

[6] The conjunction fallacy refers to the belief that multiple combined conditions are more probable than one of them in isolation even though this is not possible from a theoretical point of view (see Tversky and Kahneman, 1983).

[7] Myopic loss aversion in the context of structured product investments is analyzed in Section 3.4.

3.1.4 Cognitive Biases and Structured Product Investments

All the above-named cognitive shortcomings can strongly affect investment decisions. Due to their non-linear payoff profiles, these biases might be especially relevant when investing in structured products. As Hens and Rieger (2014) showed, structured products do not increase the expected utility of rational investors enough to compensate for the costs associated with the purchase of these products. Only when considering prospect theory, the demand for certain – but not all – types of structured products can be explained. For instance, single- and multi-asset barrier reverse convertibles [8] are among the most popular structured products even though they are highly overpriced (see Wallmeier and Diethelm, 2009). Rieger (2012) tried to explain the high demand for these products by arguing that it is mainly driven by a probability underestimation of barrier events. However, since the subjects only underestimated the probability of a barrier event for multi-asset products relative to the probability of single-asset barrier events, it only explains the popularity of multi-asset compared to single-asset barrier products. Interestingly, the estimates for the correlations between the underlying asset returns were close to the real correlations in the study of Rieger (2012), which implies that the subjects either could not apply them correctly or were exposed to the conjunction fallacy. The salience theory might provide another yet unexamined explanation for the high demand of barrier reverse convertibles due to the usually very high – and thus salient – coupon level of the products compared to the coupon level of bonds.

Ofir and Wiener (2012) examined the impact of behavioral biases in structured products investments by testing in an experimental setting whether professional investors show signs of loss aversion, the disposition effect, herd behavior, the ostrich effect, which is closely related to the confirmation bias, and the hindsight bias (also known as knew-it-all-along effect)[9], which is a distortion of the original beliefs in the direction of the actual outcome. Using hypothetical investment decisions, Ofir and Wiener (2012) showed that all the five tested biases have a significant impact in structured product investments.

[8] The holder of a barrier reverse convertible receives a fixed coupon payment plus the initial investment at the end of maturity. However, if a predefined barrier, e.g., 80% of the face value of the underlying asset, is untercut by the underlying during the product lifetime (= barrier event), the issuer has the right to deliver the underlying instead of the initial investment. In the case of multi-asset barrier reverse convertibles, the issuer has the right to deliver a underlying at his own choice given that any of the underlyings exceeded the barrier.

[9] Ofir and Wiener (2012) argued that the hindsight bias can be viewed as “the inability to correctly remember the prior expectation after observing new information”, it “hinders efficient information processing”, and is thus relevant when it comes to investments as well.

However, it is yet unknown which bias drives the demand for which product type. That question is especially important to establish specific regulations, which enable investors to buy the products they want and not the products they think they want.

3.2 Experiments in Finance

Due to the emerging research in behavioral finance, experiments are becoming more and more important in the field. The key advantage and reason for the frequent use of experiments in behavioral finance is that they allow to properly pinpoint the factor that caused a certain effect, which is usually very difficult with non-experimental research. This is possible due to the experimenter's ability to manipulate and isolate variables of his own choice. For this reason, experiments are even indispensable for certain research questions (see Huber, 2009, p. 69–71).

3.2.1 Variables and Control

One of the key features of experiments is control over variables in order to properly measure cause and effect relationships. To establish a cause-effect relationship, an independent variable (cause) is manipulated and a dependent variable (effect) is measured. If the value of the dependent variable differs for different treatments of the independent variable, then there is a causal link, given that no other factors, referred to as confounding variables, influence the relation. Thus, to properly prove that an effect results from a certain cause, it is crucial to control for confounding variables (see Stier, 1996, p. 212–215).

This can be demonstrated by the following example. Weber and Camerer (1998) wanted to find out if subjects exhibit disposition effects. Their hypothesis was that "subjects sell more shares when the sale price is above the purchase price than when the sale price is below the purchase price". The independent variable was thus the movement of the share price and the dependent variable was the reaction of the subjects, i.e., whether they buy or sell the shares. There are many possible confounding variables, which can interfere with the relation between the stock price movement and the subjects' reactions. For instance, interaction between subjects from different sessions could enable some subjects to have prior knowledge of the stock price movements in the experiment. Figure 3.2.1 illustrates the interplay between treatment effects and confounding variables in a broader context.

There are different types of confounding variables. In experimental designs with multiple

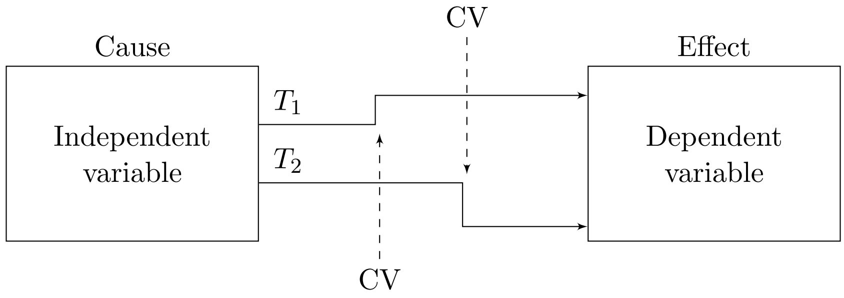


Figure 3.2.1: Treatment effects and confounding variables. This example illustrates how confounding variables (denoted by CV) can lead to a more pronounced difference between the outcomes of the treatments T_1 and T_2. Thus, the measured effect size will be greater than in reality.

groups of subjects (see between-subject design in Section 3.2.2), it is crucial to consider selection effects when the groups are different from each other with regard to characteristics that may influence the result. For example, in studies that include investment decisions the subjects' risk preferences are a key characteristic and should either be constant between groups or differences among groups should be considered in the statistical analysis. On the other hand, experiments with a single group (see within-subject design in Section 3.2.2) can also be problematic due to intrapersonal processes during the session. The exposure to a stimulus in the first part of the experiment can potentially confound the reaction to a stimulus in the second part. Thus, the ordering of stimuli can affect the outcome of the experiment. Another potential issue are changes in the measuring instrument, which can be either the experimenter, a computer or any other device. In experiments with intensive computing, a varying computer performance could be an example for such a change. Finally, relative effects of the experimental situation should also be taken into account. They occur when the subjects' knowledge of being part of an experiment affects their behavior. The results of the experimental study can only be generalized if the subjects' behavior in the experimental setting is not significantly different from their real-world behavior (see Stier, 1996, p. 213–215).

To avoid biased results, there are different ways to control for confounding variables. If the confounding variables are related to the experimental situation, it might be possible to eliminate them. Laboratory experiments (see Section 3.2.3), in particular, allow to avoid external interference, such as interaction with a third party. Where elimination is not possible, the confounding factors should at least be kept constant such that they have the same impact on the control and treatment group. In pharmaceutical experiments, for example, it is common practice that the control group also receives a medicine but without active substance (placebo).

Different methods can be applied if the confounding variables are related to the subjects' characteristics. One method is the matching of subjects from different groups. Every subject in the treatment group has a "twin" in the control group with equal characteristics. A more common method is statistical control. Relevant information on the characteristics of the subjects (such as risk preferences and others that may have an impact) is collected. Then, the differences among the groups can be considered, for instance by comparing the means of the groups using analysis of covariance or by adding the potential confounding variables as independent variables in the regression analysis.

However, it can be very costly or even impossible to collect all information on variables that might have an impact on the dependent variable. Also, it might not always be obvious which variables are potentially confounding. For these reasons, experimenters often make use of randomization. Subjects can be assigned to the different groups randomly, or the ordering of the stimuli can be determined randomly for every subject. Randomization is particularly effective if the sample is large since differences among groups are less probable in large samples.(see Stier, 1996, p. 216–218)

3.2.2 Design

Another key feature of experiments is their design. It determines the approach by which subjects are assigned to the different treatments. The validity of the results can vary substantially depending on the chosen design.

The between-subject design is the most common one. It has – next to the control group – one group for each treatment. A subject can only be part of one group and thus be exposed to only one treatment per independent variable (see Huber, 2009, p. 101–104). The assignment of subjects to groups is typically carried out randomly with one group per treatment, which is then referred to as completely randomized design (see Dean et al., 2017, p. 17). The use of multiple groups enables a clear differentiation of the effects of various treatments but with the downside of having a relatively low statistical efficiency and the risk of heterogeneous groups.

When controlling for a specific confounding variable in a between-subject design, a so-called block design can be created.[10] For example, if gender is considered as confounding variable,

[10]From a theoretical point of view, one could also apply the blocking approach to other experimental designs. However, the term "block design" is only commonly used in combination with a between-subject design.

one "block" can be created for men and another for women. When analyzing the results, the effect of the independent variable can then be measured separately for both blocks to exclude the gender impact (see Dean et al., 2017, p. 17).

In within-subject designs there is only one group of subjects, and each subject undergoes all treatments successively. Each treatment is followed by a remeasurement of the dependent variable. This design is especially advantageous if a large sample size is not available or if the characteristics of subjects influence the dependent variable. The reason for this is the guarantee of within-subject designs that characteristics of subjects are distributed identically among the treatments even in a small sample (see Huber, 2009, p. 104).

But in certain investigations the use of a within-subject design can be critical since treatments are irreversible, which means that the first treatment can have an impact on the measurement of the dependent variable after the second treatment, which is referred to as carry-over effect (see Huber, 2009, p. 173–175). As proposed above, randomization of the treatment ordering can be used to counteract these unintended effects. However, it cannot eliminate them but only ensure that all treatments are affected to a similar extent.

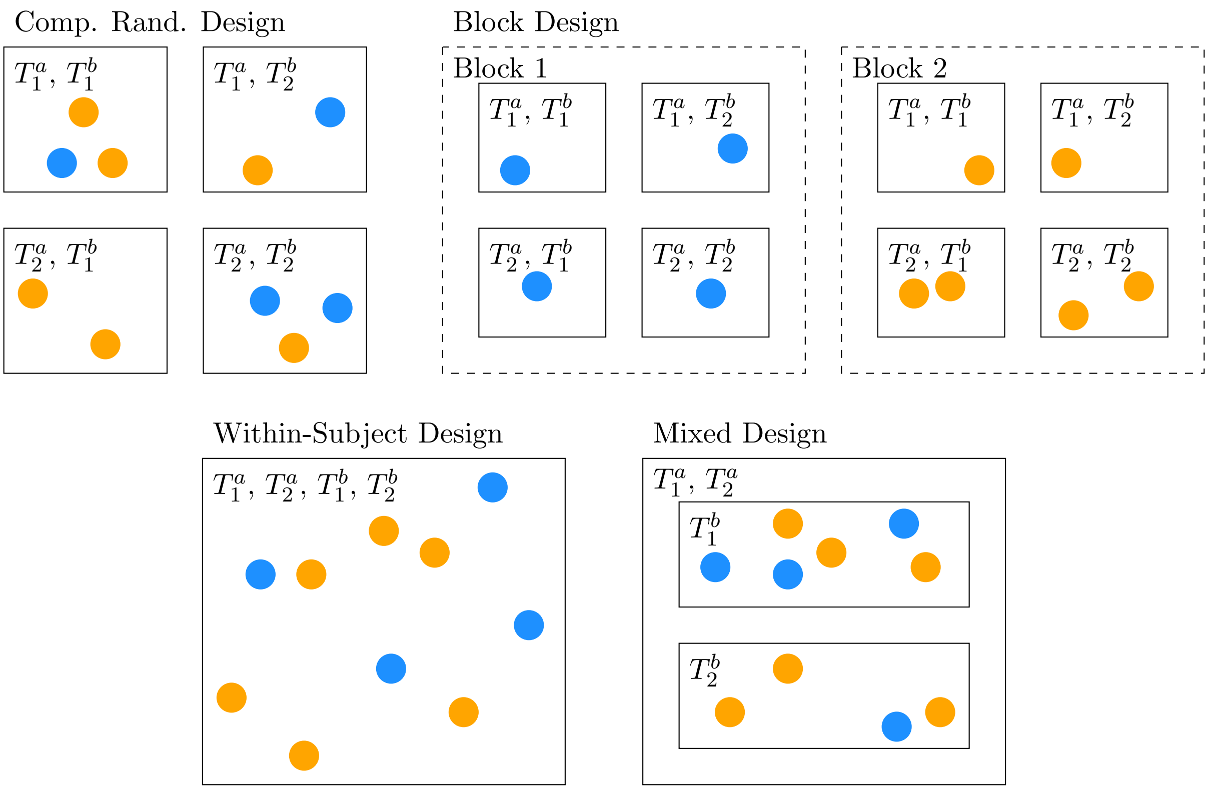


Figure 3.2.2: Experimental designs. These examples show how ten subjects (circles) can be assigned to treatments (rectangles). All designs have the same two treatments T_1^v and T_2^v for each independent variable v.

The above mentioned designs are equally applicable to experiments with more than one independent variable. In a completely randomized design, all groups would have one treatment for each of the independent variables. An experiment with two independent variables each with two treatments would result in four possible combinations and thus four different groups. In a within-group design, there would still be only one group, which is exposed to all treatments. In principle, experiments with multiple independent variables also allow for mixed designs with between- and within subject variables. Mixed designs can make sense for instance if some variables have a low risk and others a high risk of causing carry-over effects.

The assignment of subjects to treatments in experiments with two independent variables is illustrated in Figure 3.2.2.

3.2.3 Types of Experiment

Experiments can be conducted in a laboratory setting or "in the field". Laboratory experiments take place in an examination room. They allow a better control for confounding variables and provide equal or very similar conditions for each subject. However, it can be questionable if the obtained results are generalizable and applicable to natural environments and situations. The lack of generalizability is in conflict with the commonly requested requirement of external validity (for a detailed discussion of external validity, see Section 3.2.4). In contrast to laboratory experiments, field experiments take place in the natural environment of the subjects and can be applied to a real-world context, given that no confounding variables influence the outcome (see Huber, 2009, p. 77–78).

Internet-based experiments are an alternative type of experiment, which have gained more and more popularity recently. There, the entire sequence is programmed and uploaded on a server. Subjects are then able to access the experiment via internet. Typically, these experiments are also characterized by no direct contact between subject and experimenter. Greeting, instructions, and record and storage of the answers are carried out online. Subjects can be recruited, for instance, by email, online advertisement or a crowdsourcing platform[11]. This approach can have some drawbacks. Fist, since the population is not randomly drawn, the results can be biased due to self-selection as the self-selected subjects are potentially not a representative sample. Second, there is a lack of control as compared to laboratory experiments. The answers,

[11] Crowdsourcing platforms are used to outsource certain tasks, also named micotasks, which will then be performed online by a pool of volunteers or paid laborers (see, e.g., Bratvold, 2017).

e.g., age and gender, are not verifiable. third, it is often not possible to prevent multiple participations from same subjects, assistance of other persons or other interferences like television, phone calls and the condition of the subjects. However, if it can be assured that the internet experiment does not deliver significantly different results than the laboratory counterpart, they can also have advantages. For instance, the sample can be increased with little additional effort. Also, the Rosenthal effect, which refers to the impact of researcher expectations on the outcome (see, e.g., Huber, 2009, p. 184–187), can be avoided.[12] Other advantages are the standardized procedure and the convenience for subjects of being able to execute the experiment at any time they want (see Huber, 2009, p. 78–80).

3.2.4 (Other) Methodological Challenges

Next to the control for confounding variables, the experimental design and the type of experiment, I want to point out a few other selected issues that are crucial for the studies presented in the subsequent sections and potentially also for other experimental research in finance.

One of the most important concerns of experiments is its internal and external validity. Validity in general refers to the suitability of a test or measurement method – such as an experiment – to measure what it is supposed to measure. The internal validity is limited if there are inferences within the experiment. An experiment is internally valid if the measured effect results only from the dependent and not from confounding variables. The smaller the influence from confounding variables, the higher the internal validity. Several examples where the internal validity is impaired have already been given in the previous subsections, as for instance the Rosenthal effect, the carry-over effect or unintended/uncontrolled differences among groups in a between-group experimental design. Internal validity is also a prerequisite for external validity. External validity is given if an experiment can be generalized to other people, places and situations and can thus be applied to the real world. The subject's knowledge about the participation in the experiment can already cause him or her to behave differently than in reality (see Huber, 2009, p. 149).

Experiments in finance often include hypothetical investment decisions, which might be

[12] Rosenthal and Fode (1963) gave each student five rats to measure the rats' time to traverse a maze. One half of the students was informed that their rats are particularly intelligent while the other half of the students was informed that their rats are not intelligent. The measured performance of the rats from the first group was significantly better even though all rats were of similar intelligence. The results were unconsciously biased by the expectations of the students.

blamed for not being externally valid. In this regard, the use of monetary incentives is a controversial solution. Some economists state that results from experiments in finance cannot be applied to the real world if subjects receive no payment according to their answers. They argue that subjects behave differently when nothing is at stake (see, e.g., Smith and Walker, 1993). Accordingly, in many academic journals monetary incentives have virtually become a prerequisite for publishing experimental research in the field of finance. Kachelmeier and Shehata (1992) showed empirically that very high rewards (up to three times of the subjects' normal monthly revenues) indeed lead to significantly different decisions. However, as Kachelmeier and Shehata (1992) found, there is hardly any difference between a low monetary incentive – as in a typical experimental study in finance – and no monetary incentive. Some critical voices also claim that providing real payoffs still does not create a real-world setting. While for instance real decisions involve gains and losses, one can hardly enforce real losses in a laboratory. Moreover, hypothetical decisions that involve high amounts of money can be easily implemented, but decisions incentivized with high real payoffs usually cannot (see Read, 2005). Or, as Read (2005, p. 273) stated, "real-world behavior is better exemplified by realistic hypothetical choices than unrealistic real ones".

Another important issue is the sample size. It is important to fix the sample size before running the first experiment session to avoid a(n) (unconscious) continuous increase of the sample until a significant result is achieved. A common approach to determine the required sample size ex ante is the use of the power of a statistical test. Experimental research usually wants to find out whether the mean of the dependent variable μ_i of the treatment i differs from the mean of the control group μ_0 statistically. Given the null hypothesis $H_0 : \mu_i = \mu_0$ and the alternative hypotheses $H_1 : \mu_i \neq \mu_0$ or rather $H_1 : \mu_i - \mu_0 = \Delta$ for all i, then the sample size can be seen as a function of the effect size Δ, the statistical power, the number of treatments, the significance level and the error variance. Thus, if all these parameters are known, the sample size can be easily calculated. While the power, the effect size Δ, the number of treatments and the significance level are chosen by the researcher, the error variance needs to be estimated by means of prior beliefs, previous studies or a pilot study (see Dean et al., 2017, p. 45–49).

3.3 Perceived Attractiveness of Structured Products – The Role of Presentation Format and Reference Instruments[13]

3.3.1 Introduction

The variety of structured products has increased strongly since their inception in the early nineties, and some of the most popular products have a complex, nonlinear payoff structure. Whereas new products have become increasingly complex, the way they are presented – typically by means of a simple payoff diagram and a verbal description of the investment risks involved – has hardly changed.

In recent years, following a proposition of the German Derivatives Association and the Swiss Structured Product Association, a risk score was introduced in Germany and Switzerland, which is now available for most of the structured products traded on the Swiss and German exchanges. The score ranges from 1 to 5 in Germany and from 1 to 6 in Switzerland. It is based on a value-at-risk (VaR) approach using historical simulation with daily returns, a confidence level of 99% and a holding period of ten days (DDV, 2017; SVSP, 2015). This risk score appears to be easy for even inexperienced investors to grasp. However, VaR does not capture the particular shape of the return distribution of structured products, and the holding period of ten days does not correspond to the typical investment horizon, which is much longer. Therefore, VaR is of limited use in characterizing the risk-return profile of structured products.[14]

The low transparency in the market makes it difficult for investors to correctly assess the risk involved. When the structured products issued by Lehman Brothers defaulted in the wake of the bank's bankruptcy, it became evident that many investors had not been aware of the credit risk involved. Prior research also provided evidence that investors generally do not have a balanced view of products' risk and return characteristics (Lindauer and Seiz, 2008; Rieger, 2012; Rieger et al., 2014; Wallmeier and Diethelm, 2009, 2012). The issuers might even have an incentive to choose a product design that exploits the behavioral biases of investors (Ofir and Wiener, 2012; Hens and Rieger, 2014; Kunz et al., 2017). However, it is yet unclear how to present

[13]This section was prepared in collaboration with Martin Wallmeier.

[14]See Cao and Rieger (2013) for an extended discussion on the limitations of VaR as a risk measure for structured products.

complex risk and return profiles to avoid such biases and to improve investment decisions from an investor's point of view. This question is also important because a new regulation requires the issuing banks to present a product's risk and return profile in its "Key Information Document", without specifying the presentation format (PF).

A natural way to illustrate this profile would be to complement the payoff diagram with information on the payoff's probability distribution, as we show in Section 3.3.2. This approach has been followed in asset allocation studies (see, e.g., Weber et al., 2005) but not in investment decisions about structured products. This extension is the focus of our study.

Our first research question is whether investors perceive the attractiveness of structured products differently when the payoff profile is complemented with an illustration of the payoff probability distribution, and whether the way in which the probability distribution is shown matters. We hypothesize that the probability distribution is important and allows for a better understanding of the risk-return profile than the payoff diagram and verbal descriptions alone. The presentation must be intuitive and easy to comprehend.

Our second research question is whether an adequate illustration of probability distributions helps investors differentiate between a particular structured product and a simpler strategy in which the underlying asset is combined with a risk-free asset to achieve a similar combination of risk and return. We hypothesize that one reason for the perceived attractiveness of structured products is that they are evaluated with respect to an inadequate reference instrument. For example, payoff diagrams and verbal descriptions often compare a capital protection product (CPP) with a pure investment in the underlying asset. If investors prefer the CPP in this comparison, this might simply indicate a preference for lower risk. Thus, a suitable reference point would be a combination of the underlying asset with a risk-free asset. The PF can help to highlight the remaining differences and identify the better alternative.

To study our research questions, we conduct two experiments, both of which use a similar design. In the first part, the participants evaluate different financial instruments after having been introduced to them with one of three PFs. In the second part, they have the possibility to design their individual structured product from a wider range of possibilities. Simply by adapting a few parameters, they can reconstruct the payoff profile of most of the product categories from the Eusipa derivative map in a straightforward way (see Eusipa, 2019a). In the third part, we combine the underlying asset and a risk-free asset in such a way that the portfolio has the same volatility as the structured product individually designed in the previous step and let the participants rate this portfolio with respect to their individual product. If participants were indifferent between the alternatives, this would mean that a simple combination of underlying and risk-free asset is sufficient to provide the desired risk-return combination.

Our intended contribution to the prior literature is threefold. First, we present a flexible framework for designing tailor-made structured products, which allows us to implement part of the experiments as an interactive exploration. Second, we study the importance of the PF by comparing the main types of structured products available in real markets. This comparison spans a wider range of nonlinear payoff profiles than previous studies. Third, the role of the reference instrument and the case for displaying it in risk-adjusted terms have not gained much attention in the literature so far. Overall, our findings can be used to improve information documents for investors.

3.3.2 Presentation Formats

This section deals with two main problems. One of them is the way financial products – in particular their risk and return characteristics – are presented. The other is the role or impact of the PF, i.e., if investor preferences for certain products vary when displaying the products differently. Both questions have already been addressed in the literature. This section includes a review of the main findings from the literature and introduces the PFs used in our study.

Presentation Formats Proposed in the Literature

The most convenient way to present the functioning of options or financial products with option components are payoff diagrams. A payoff diagram is a graphical illustration of the potential outcome of the financial product at maturity. It shows the loss or profit of the product at maturity as a function of the price of the underlying asset at maturity. It facilitates the understanding of such products a lot as the functioning is usually comprehensible at a glance. However, it does not show how probable the displayed outcomes are. A call option, for instance, seems to be very attractive compared to its underlying when looking at the payoff diagram alone because it has a similar profit potential at a much lower price and the loss is limited to the option premium. The call option performs much better if the price of the underlying drops excessively, and there is no essential difference if the price is constant or increases. However, the case where the call option performs (much) better than its underlying is usually unlikely, which is not apparent from the diagram.

This example shows that payoff diagrams do not allow to draw any conclusions regarding the value of the product. Nonetheless, we think that investors often ignore this fact and make investment decisions without any information on the probability distribution of the return of the underlying but simply by means of a subjective opinion of the future price development. This is especially problematic since these opinions are subject to behavioral biases (see Section 3.1). For this reason, it is essential to provide more sophisticated illustrations that include probabilities of the outcomes – especially for products with non-linear payoff profiles.

Wallmeier (2011) provided a variety of different ways to display a more complete picture of the return and risk of financial products. One of them are return histograms. Histograms are commonly used in statistics and a natural way to display the distribution of numerical data. The range of different returns[15] is divided into intervals. The number of returns within these intervals determines the probabilities that the future return will end up within the thresholds of the intervals. The outcome is an estimation and discretized version of the probability density function.

Another proposed illustration is a bar chart with a certain number of representative returns. The return distribution is split into equally sized quantiles, all of which have the same probability. Then the expected return is calculated for each quantile. These returns are sorted and displayed in ascending order. Wallmeier (2011) proposed to split the distribution into fifty quantiles such that each return represents a probability of 2%.

Both of these illustrations clearly show the up- and downside potential of financial products. For example, they reveal that call options might not be as attractive as they appear to be when considering only their payoff diagram. In the histogram, the interval that includes the negative call premium would be very salient due to its high probability as compared to the other intervals. The bar chart with ordered returns would include a high number of (slightly) negative returns that equal the call option premium.

Another PF provided by Wallmeier (2011) is a rolling dice analogy, which is very similar to the bar chart with ordered returns with the exception that the number of quantiles is six. Furthermore, numerical information can be shown to improve the transparency. Some of the most common and easily understandable risk and return measures are for instance expected

[15]These returns can either be historical returns or obtained by Monte Carlo simulation.

return, volatility, loss probability, VaR and beta coefficient. To compare structured products to the market risk-return tradeoff, they can be displayed on the security market line in the capital asset pricing model[16]. The last proposition is a measure of the degree of active orientation of a portfolio including the structured product. It indicates the utility loss due to losing diversification as a function of the structured product's weight in the portfolio.

A PF that has gained much attention in recent literature is experience sampling (see, e.g., Kaufmann et al., 2013; Bradbury et al., 2015; Hogarth and Soyer, 2015). Experience sampling is an interactive risk simulation approach where potential investors randomly draw returns from the financial product's return distribution. Typically, they can draw as many returns as they want, whereas each return adds up to the existing ones and helps to build up the return distribution. Experience sampling enables investors to experience and improve the understanding of the return distribution with every draw. But, strictly speaking, experience sampling does not provide investors with additional information compared to a simple graphical display of the return distribution. In fact, experience sampling provides even less information if the number of sampled returns is small. In that case, investors risk to end up with an incomplete or even unrepresentative return distribution. However, some decision makers – especially those with low proficiency in statistics – may find it easier to understand an "experienced" return distribution.

Impact of the Presentation Format on Investment Decisions

Weber et al. (2005) examined the impact of the display of a probability density function and a bar chart with historical returns in chronological order on investors' asset choices and their assessments of the risk involved. The investment alternatives included different stock indexes, single stocks, government bonds and combinations of these instruments. Subjects had to assess the risk on a scale and estimate return and volatility of each investment alternative as well as compile their own portfolio consisting of these investment alternatives. While estimated returns were in line with historical expected values, predicted volatility significantly varied across the two different PFs. Subjects that were assigned to the PF with the density function predicted a greater volatility than subjects assigned to the PF with the bar chart with historical returns. The perceived risk was similar for both formats; but since subjects rated the perceived risk relative to the other products, it is not clear whether absolute perceived risk level differs between these

[16]Since the standard capital asset pricing model is not applicable to assets with non-linear payoff profiles, a modified beta coefficient and model as introduced by Leland (1999) is used.

PFs. In any case, the fact that different PFs led to a different estimated volatility shows that the way investment products are presented matters and can affect investment decisions.

Vrecko et al. (2009) analyzed how the PF affects the revealed skewness preferences of investors. Using combinations of (leveraged) stocks, (short) calls and a risk-free asset, they constructed an equity index with a symmetrical return distribution (no skew), a product with a left-skewed distribution and a product with a right-skewed distribution. All three products were identical in terms of risk, i.e., they had the same return volatility but differed in terms of skewness. They found that the PF had a significant impact on the skewness preference. The display of probability density functions led to a pronounced preference for the left-skewed product.[17] Bar charts with representative returns also seem to result in a slight preference for negative skewness. Cumulative distribution functions, on the other hand, seem to increase the preference for right-skewed products.

Döbeli and Vanini (2010) tested whether easily understandable explanations of structured products are effective. Subjects were confronted either with traditional, rather technical term sheets or with fact sheets that explained the products in simple terms. The main finding was that the simple fact sheets highly encouraged people to invest, especially first-time buyers and women. This conclusion resulted from both a questionnaire with hypothetical products and a field experiment with real products.

Kaufmann et al. (2013) compared multiple PFs, i.e., numerical information, density function, experience sampling and a combination of the density function and experience sampling named "risk tool" in an asset allocation decision with a stock index and a risk-free asset. They found that the willingness to invest in the risky stock index increases when using the risk tool. Furthermore, this result seems to be driven more by experience sampling than the density function. They argued that the increased risk taking can be explained by higher confidence, reduced risk perception and avoided overestimation of the loss probability. However, it is not entirely clear why increased risk taking is driven more by experience sampling. One explanation could be that extreme losses are not experienced at all in this PF because they have a very small probability and the number of draws is typically rather low[18].

[17] As Ibrekk and Morgan (1987) showed, people tend to regard the mode of a probability density function as the mean (or in this case the expected return), which could be a possible explanation for the pronounced preference for the left-skewed product in this case.

[18] On average, the amount of draws was 14.5. Consequently, it is likely that extreme losses were not sampled in many cases, which could have led subjects to underestimate the occurrence of extreme losses.

Bradbury et al. (2015) confirmed the relevance of experience sampling in a setting in which the number of draws was fixed, and the sample, by construction, reproduced the shape of the underlying distribution. In two stages, the subjects were asked to choose between structured products with capital protection levels from 0% to 100%. The first-stage decision took place after showing a verbal description and a payoff diagram; the second-stage decision occurred after an additional experience sampling. More than half of the subjects changed their initial product choice, and most of them switched to a riskier product.

In summary, one can say that there are several studies that support the importance of the way financial products are displayed. Probability density functions, bar charts with representative returns and simulated experience seem to be the most effective and comprehensible PFs for investors. Most of the studies, however, focus on conventional assets, such as stocks, indexes or bonds, and only very few studies incorporate structured products. But due to their non-linear payoff structures it is questionable whether previous findings can be applied to these products. To our knowledge, ours is the only study that tests the impact of "printable" PFs, which could be included for instance in term sheets, on structured product investments.

3.3.3 Designing Tailor-made Structured Products

In a part of our experiment, the participants were asked to design their own structured product. By specifying the three parameters minimum payoff, maximum payoff and slope of the straight line between the minimum and maximum payoffs (see Figure 3.3.1), a multitude of different structured products could be created. The minimum payoff allows to protect investors from a loss that exceeds an acceptable limit. The downside of a high capital protection level is that the designed product performs worse than the equivalent product with a lower capital protection level if the development of the underlying stock price is favorable. When limiting the maximum payoff, one can benefit from a lower loss in the event of an unfavorable development of the underlying stock price. These two parameters alone allow to reconstruct a reverse convertible (RC), when limiting only the maximum payoff, a CPP, when limiting only the maximum loss, a stock, when employing no limits, or a collar, when limiting both the maximum loss and profit. Finally, the slope between minimum and maximum payoff enables to participate disproportionally in price changes of the underlying stock price. This feature might be interesting particularly for investors that favor a linear profile but still prefer to increase the expected return or to decrease

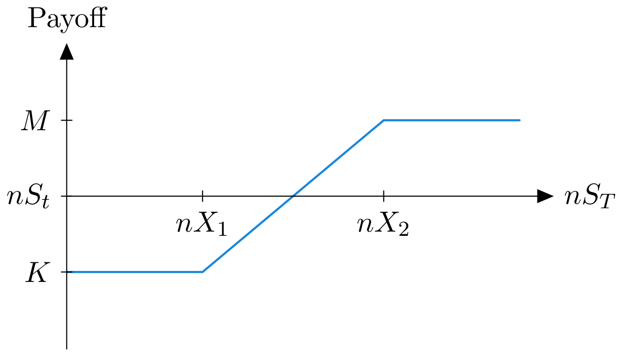


Figure 3.3.1: Payoff diagram of a collar

risk.

On this basis, the thresholds between the three sections of the payoff diagram are determined in such a way that the product value is equal to 10 000. Technically, the resulting profile corresponds to a collar instrument, which can be decomposed into a long position in the underlying stock, a long put option with a strike price X_1 and a short call option with a strike price $X_2 > X_1$. The instrument is sufficiently flexible to include our previous products as special cases: the collar is equal to a stock investment for $X_1 = 0$ and $X_2 \to \infty$; it corresponds to a CPP for $X_1 > 0$ and $X_2 \to \infty$ and to a RC for $X_1 = 0$ and limited X_2.

We use the following symbols for the formal derivation of the collar: T is the investment horizon and $t \leq T$ the valuation time; S_t is the share price of the underlying stock and $C_t(X)$ and $P_t(X)$ are the values of calls and puts, respectively, with strike price X and time to maturity $T-t$. We define n as the number of shares of the underlying stock that have an aggregate value of 10 000: $n = 10\,000/S_t$. Finally, A_t is the risk-free investment at time t, and r is the risk-free interest rate (continuously compounded).

The participants specified three parameters: The minimum payoff $K \geq 0$, the maximum payoff $M > K$ and the slope s in the middle section of the payoff diagram ($X_1 < S_T < X_2$). The corresponding collar can then be derived from three formal conditions.

The first condition is to achieve the specified slope s, which means that the collar must include ns shares of the underlying stock. The slope is then equal to (see Figure 3.3.1)

$$s = \frac{M - K}{n\,(X_2 - X_1)}, \tag{3.1}$$

which is equivalent to

$$X_2 = X_1 + \frac{M - K}{sn}. \tag{3.2}$$

The second condition is to ensure the minimum payoff K in case of $S_T \leq X_1$. In this case, the put option is exercised, while the call option expires worthless. Thus, the value of the stock position, the put option payoff and the risk-free asset at T must add up to K as follows.

$$snS_T + sn\left(X_1 - S_T\right) + A_t e^{r(T-t)} = K. \tag{3.3}$$

The third condition requires that in the case of $S_T \geq X_2$, the aggregate value of the stock position, the short call and the risk-free asset is equal to the maximum payoff M.

$$snS_T - sn\left(S_T - X_2\right) + A_t e^{r(T-t)} = M. \tag{3.4}$$

Solving Eq. (3.3) for A_t gives

$$A_t = \left(K - snX_1\right) e^{-r(T-t)}. \tag{3.5}$$

This is the same value that we obtain when solving Eq. (3.4) for A_t and inserting X_2 from Eq. (3.2).

Finally, the time t value of the collar must be equal to the investment amount of 10 000 as follows.

$$snS_t + snP_t(X_1) - snC_t\left(X_1 + \frac{M-K}{sn}\right) + \left(K - snX_1\right) e^{-r(T-t)} = 10\,000 \tag{3.6}$$

We solve this equation for the only unknown, which is X_1. Thus, the collar is unambiguously specified. When the participants changed their input parameters, the calculations were rerun and the collar was adjusted accordingly.

Our approach is related to other tools proposed in the literature. In the "distribution builder" of Sharpe et al. (2000), Goldstein et al. (2008) and Sharpe (2011), subjects could build and explore different probability distributions for end-of-period wealth by arranging 100 markers on a digital board. Only distributions that satisfied a given budget constraint were allowed. The cost of different marker positions was derived from an equilibrium asset pricing model. This builder was designed for a single use to find the best distribution; it is less suitable for our study, which requires repeated comparisons of different shapes of distributions.

Rieger and Hens (2012) proposed a tool for designing structured products in which people were able to create their own desired payoff profile as the connecting line of a number of points that could be moved on a touch screen. After each move, the payoff profile was automatically shifted upwards or downwards to ensure the budget constraint was applied. While this tool allows for almost any shape of the probability distribution, our builder focuses on conventional payoff profiles within the scope of the Eusipa derivative map.

3.3.4 Experimental Design

In order to test the impact of the PF on structured product investments, we used a between-subject design, where the PF was modeled as between-subject variable. We believe that the impact of the PF is best analyzed using a between-subject design due to the use of irreversible treatments. E.g., when showing a certain PF to assess the attractiveness of financial products, one cannot expect subjects to ignore and forget the information provided in the subsequent stage when assessing the attractiveness of the same products using another PF. There would be a major risk of having carry-over effects. In order still to ensure comparability among groups, subjects were assigned randomly to the three groups to avoid systematic heterogeneity and potential confounding variables, such as the subjects' risk preferences, financial experience, gender and income, are considered in the statistical analysis.

Presentation Formats and Treatments

We employ three different PFs in our study. The first format (PF 1) consists of payoff diagrams and was shown to all groups of subjects equally. The payoff diagrams used in the study are similar to those used by Eusipa and many issuers with one noteworthy difference. Eusipa and the issuers typically show a stylized payoff diagram for all products within a product group, for example, RCs. Thus, specific product characteristics such as the coupon rate are not apparent. To ensure that the products are correctly displayed, we always used the specific parameters of the presented products. Figure 3.3.2 shows the payoff diagrams of Experiment 1 (left side) and Experiment 2 (right side) for three products: a stock investment (upper graph), a CPP (middle graph) and a RC (lower graph).

The stock of the first graph is also the underlying asset of the CPP and RC. It has a linear payoff profile. The upside potential is not limited and the downside potential is limited to the initial investment. Theoretically, the price of a stock can drop to zero or increase to infinity in extreme cases. This does not apply to the other two products. Both of them are structured products and depend on the development of the underlying stock price. CPPs have a limited loss. The final payoff at maturity cannot be lower than the predefined capital protection level

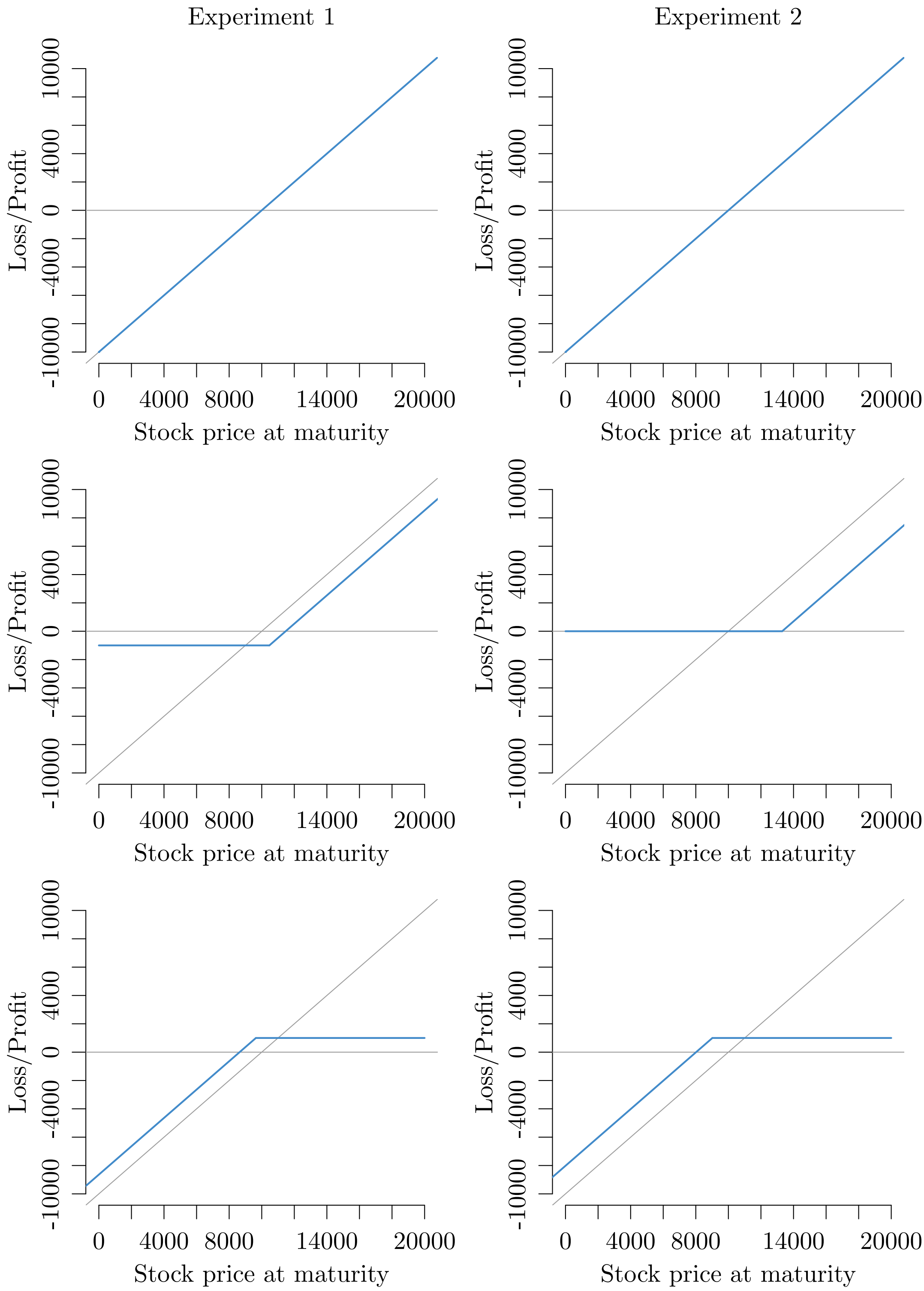


Figure 3.3.2: Payoff diagrams of the three base products (stock, CPP and RC) from the first (left) and second (right) experiment. The blue lines represent the payoffs of the three products. The gray, diagonal lines represent the payoffs of the underlying asset.

even if the development of the underlying stock is unfavorable. In exchange, the profit in the case of a favorable development of the stock price is lower compared to holding the stock. The RC has a limited upside potential. This implies that the payoff at maturity cannot exceed a certain predefined threshold even if the underlying stock performs very well. But in the case of an unfavorable stock development, the loss is lower than the loss of holding the stock. The product is basically similar to a fixed rate bond with the additional feature that the issuer has the right to deliver a predefined number of shares of the underlying stock instead of the face value. The product's name "reverse convertible" is derived from this feature.

The value of the stock investment at the maturity is shown on the horizontal axis of the payoff diagrams. All products are designed such that they have an initial value of 10 000. The RC provides a coupon of 10%, so that the maximum profit is 1 000. The CPP has a minimum payout that is 10% below (as used in Experiment 1) or equal to (as used in Experiment 2) the initial investment.

In the current zero interest rate environment, the minimum payoff of a CPP is necessarily lower than the initial investment. Otherwise, there would be an arbitrage opportunity because a product that guarantees a repayment of 100% and still offers some upside potential would clearly be superior to a risk-free asset with an interest rate of zero. Our first experiment is based on the current interest environment and correspondingly assumed a capital protection level of only 90%. A serious shortcoming of this setting is that the results might be driven by an aversion of investors against likely losses. Loss probability aversion is a phenomenon that is well known in practice (Rieger, 2016) and also well documented in the recent literature (Zeisberger, 2016). Therefore, our results for the CPP might not be applicable to situations in which the issuers can provide a guarantee level of 100%. To account for this concern, we repeated the first experiment (Experiment 1) with a new population of subjects for a risk-free interest rate of 4% and a capital protection level of 100% (Experiment 2). We hypothesize that PFs that make the loss probability of the CPP clearly visible will lead to a downgrade of the product in Experiment 1 but not in Experiment 2.

While the first group, which serves as control group, was only confronted with the payoff profile of PF 1, other groups got to see additional information. The second illustration used in our study (PF 2), which was assigned to the second group of subjects, included probability histograms as shown in the left graphs of Figure 3.3.3 (Experiment 1) and Figure 3.3.4 (Ex-

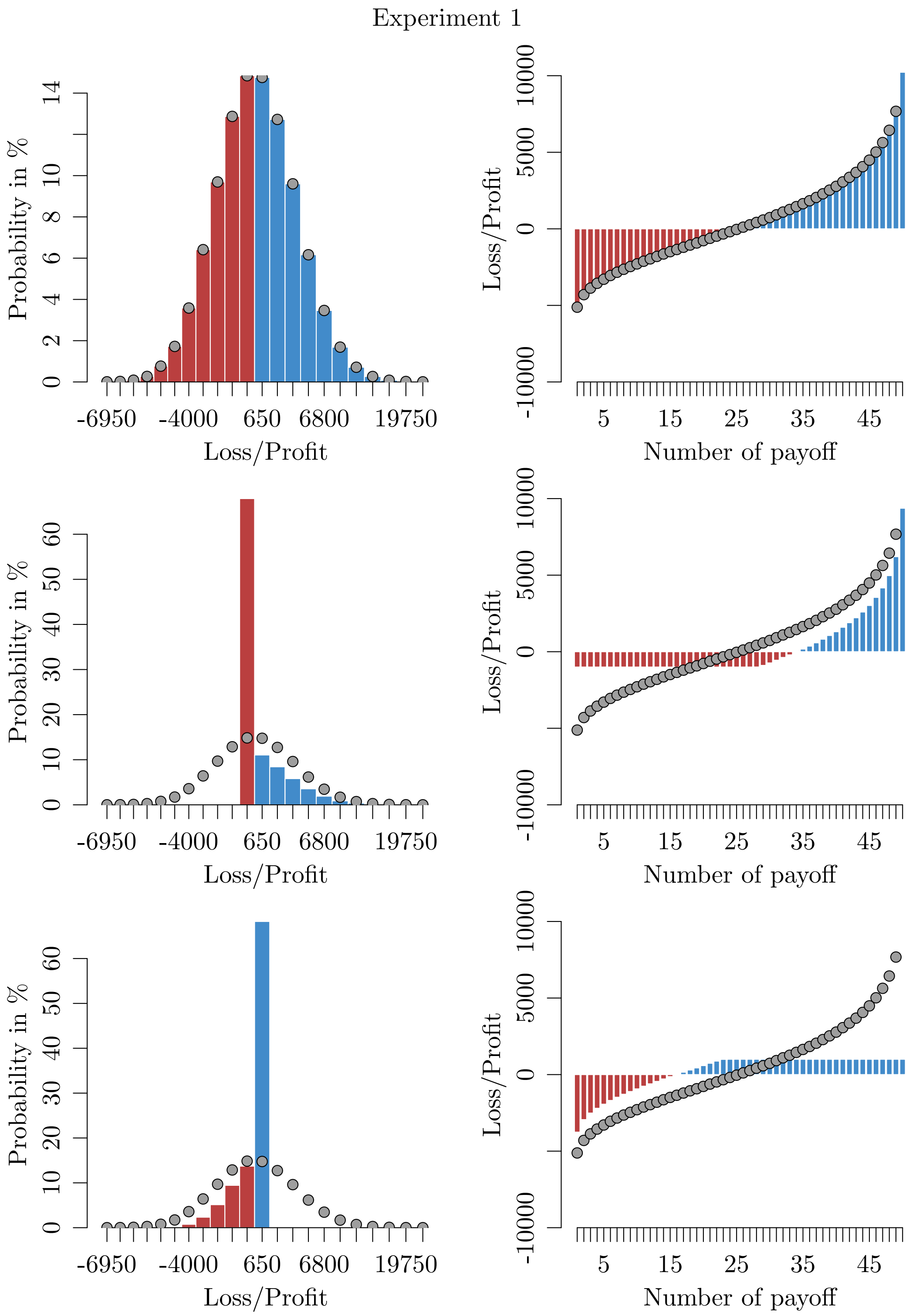


Figure 3.3.3: Risk and return characteristics of the three base products (stock, CPP and RC) from the first experiment illustrated with histograms (left) and charts with fifty ordered payoffs (right). The gray dots represent the underlying stock.

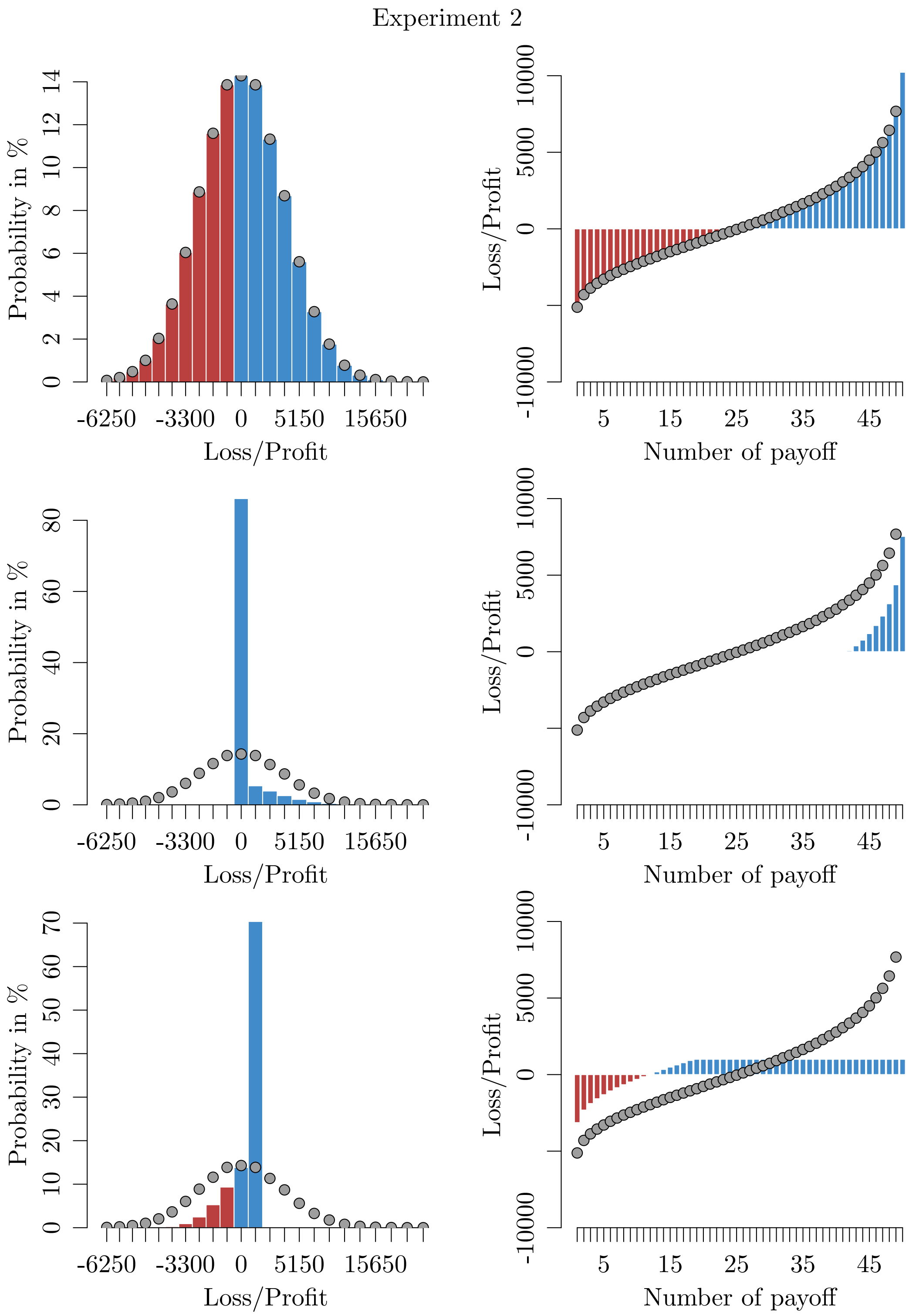


Figure 3.3.4: Risk and return characteristics of the three base products (stock, CPP and RC) from the second experiment illustrated with histograms (left) and charts with fifty ordered payoffs (right). The gray dots represent the underlying stock.

periment 2) for the same three products as before. This diagram represents the most common way of presenting probability distributions. The horizontal axis indicates the gains and losses in dollar amounts, and the vertical axis indicates the probability of a gain or loss falling into the interval of the respective bar. To facilitate the risk and return comparison, gains are shown in blue, while losses were shown in red. For a better comparison, all graphs in Figure 3.3.3 and Figure 3.3.4 included the outcome of the underlying stock investment in grey dots.

The third and last illustration used in our study (PF 3), which was assigned to the third group of subjects, is a bar chart with fifty ordered payoffs as shown in the right graphs of Figure 3.3.3 and Figure 3.3.4. Each ordered payoff represents a probability of 2% and is defined as the expected value over the respective interquantile range. To explain the diagram, investors could be told that buying this product is similar to drawing from an urn with 50 balls, where the values on the vertical axis show which values of profit or loss the balls represent. It is important to note that this diagram includes more information than the payoff diagram but is nevertheless somewhat similar. For example, the straight line for the stock investment in PF 1 becomes a curved but still monotonically increasing profile in PF 3. The maximal loss of CPP and the maximal gain of RC are visible in PF 3 in the same way as in PF 1; the only difference is that in PF 3, the exact probability of this maximal loss or gain can be inferred from the number of bars with this value. It is not clear whether this will be important additional information for investors. Due to the similarity in profiles between PF 1 and PF 3, we might suspect that the added value of PF 3 is small.

All graphical illustrations also include the outcome of the underlying stock in light grey lines (payoff diagram) or dots (histogram and chart with ordered payoffs) to improve the visual comparability. We assume an expected stock excess return of 5% p.a. over the risk-free rate, a return volatility of 30% p.a. and an investment horizon of one year. Mean payoffs or payoff standard deviations were not plotted in the illustrations of the experiments to avoid manipulation of preferences towards a specific moment. We further assume that the stock return is log-normally distributed, as it is in the Black-Scholes model. Thus, we ignore stochastic volatility, jumps and fat tails. These factors are important for option pricing but less so in a comparison of the return distributions of different types of products. The characteristic shapes of the return distributions of the CPP and RC are so different that the details of the return generating process do not play an important role in our graphical displays.

Several reasons led to the inclusion of the above named PFs or the exclusion of other PFs respectively. First, the effectiveness of histograms and ordered, representative payoffs is supported by Vrecko et al. (2009). They found that probability density functions and charts with ordered, representative returns are preferred among subjects in terms of decision usefulness. PFs that were reported to be less useful are cumulative distribution functions, randomized bar charts (same as the chart with ordered returns but the order is randomized) and a quantile graphic[19].

Second, alternative illustrations may lead to a biased view of the products' risk and return. As shown in Hertwig et al. (2004), rare events are overweighted in decisions from numerical information and underweighted in decisions from experience. The latter was explained with "reliance on relatively small samples of information and overweighting of recently sampled information" by the authors. Thus, it is difficult to apply experience sampling in the context of structured products with their highly non-linear return profiles, as a large number of drawings would be required to capture the particular shape of the return distribution. In our experiments, the process would have also been cumbersome as it would had to be repeated for several products. With regard to numerical information, we furthermore argue that common risk measures such as VaR or standard deviation are difficult to explain if investors are unfamiliar with statistics or finance. From this perspective, graphical displays of return distributions seem to be superior to numerical information and experience sampling to illustrate structured products.

Procedure

In the first step of the experiment, after receiving some basic instructions, we collected information about the subjects' financial knowledge and experience. Specifically, subjects were asked about their familiarity with statistics and structured financial products and whether they had already invested in structured products, stocks, mutual funds, bonds or derivatives.

In the next step, the subjects' risk preferences were identified. For this purpose, we used five different measures. The first two measures represent certainty equivalents for hypothetical lotteries derived from Rieger et al. (2014), where we determined the subjects' willingness to pay either to participate in a lottery with gains or to avoid a lottery with losses. The latter was used to elicit subjects' risk preferences in the domain of losses. The other three measures were taken

[19]This graphic shows the monthly development of the 5%, 50% and 95% return quantiles of an investment product. However, only the quantiles at a particular point of time were relevant for the decision situation under study because the investment period was fixed.

from the domain-specific risk-taking (DOSPERT) scale of Blais and Weber (2006). While this scale contains multiple questions to assess risk attitudes in different domains, we only considered those related to investment decisions. In these questions, subjects were asked to indicate the likelihood of investing a certain percentage of their annual income in different alternatives on a seven-step scale. The five risk attitude measures, together with the four experience measures, are used as control variables.

The main part of the experiment consisted of three investment choices. For the first decision, the subjects were introduced to three investment products using the graphical display of their assigned PF. These products were identical to the three hypothetical products presented in Section 3.3.4, namely, a stock, a CPP with a minimum payoff of 90% (Experiment 1) or 100% (Experiment 2) respectively and a RC with a maximum payoff of 110% of the initial investment amount. The stock served as the underlying asset of the CPP and RC. Owing to its essential role, the stock was always displayed first on the left side. The order of the two structured products was then determined randomly. To measure the perceived attractiveness of the three products, we applied two different measures. First, the subjects were asked to rate the attractiveness of each product on a five-step scale from very unattractive to very attractive. Second, the attractiveness was determined in a hypothetical investment decision, where the subjects could allocate an investment budget of CHF 10 000 over an investment period of one year.

In the second investment decision, the participants designed their own structured product based on the collar framework presented in Section 3.3.3. They were again asked to imagine having to invest an amount of CHF 10 000 in the created product for one year. As a consequence, the subjects designed the most attractive product according to their perception based on the assigned PF. The starting point of the individual product design was a product with a linear payoff profile. Using sliders, the participants could change the minimum payoff within a range of 0% to 100% of the investment amount, the maximum payoff within the range of 100% to 200% of the invested amount, and the slope between the minimum and maximum payoff within a range of 0.2 to 3.2. On the basis of these input parameters, the threshold values between the three sections of the payoff profile were determined as presented in Section 3.3.3 (X_1 according to Eq. 3.6 and X_2 according to Eq. 3.2). The resulting collar was displayed in the graphs of the assigned PF. The changes could be seen in real time. The graphs reacted smoothly to the slider control so that the participants could explore the effects of the input parameters.

In the third investment decision, the individually designed product was compared to a linear product with the same volatility. This linear product consisted of a simple combination of the stock and the risk-free asset. The underlying idea is to introduce a reference instrument that entails a similar risk in terms of return volatility as the structured product. In the previous graphs, the underlying stock without risk adjustment always had served as a reference instrument (see the grey, diagonal lines in Figure 3.3.2 and the grey dots in Figures 3.3.3 and 3.3.4). This is in line with generally accepted practices. However, compared to this reference point, a CPP might look attractive not because of its particular payoff structure but because of its lower risk compared to the underlying stock. For this reason, we tested whether the perceived attractiveness of the tailor-made product survives when the alternative is to adjust the risk level of the linear profile in the most simple way.

As in the first investment decision, the subjects rated the perceived attractiveness of both products on a five-step scale before they set the investment weights in a hypothetical investment decision with a budget of CHF 10 000 and an investment period of one year. The individual product was introduced as new structured product; we did not reference it as the individual product of the previous part because the participants might have otherwise tended to adhere to their earlier choice even if this new product was inferior in light of the new situation. The placement of the two products (left or right on the screen) was again determined randomly.

We incentivised participants with monetary compensation for each investment decision. In the compensation scheme, the hypothetical investment budget of three times CHF 10 000 was broken down to three times CHF 5. To calculate the subjects' payoffs, the returns of the three investment choices were simulated and applied to the base value of CHF 5.

In the last step, subjects were asked about different demographic attributes, such as age, income, education, profession and gender. These attributes are used as additional control variables in our statistical analysis. Appendix B.1 gives an overview over all variables included in the study. Appendix B.2 shows screenshots of the different stages of the experiment. The second experiment had the same design. The only differences were a higher risk-free interest rate (4% instead of 0%) and a higher protection level of the CPP in the first investment decision (100% instead of 90%).

3.3.5 Participants

To identify the required number of participants with our experimental design, we conducted a power analysis based on our regression models using the software G*Power 3 of Faul et al. (2007). For a medium standardized effect size of 0.15 (Cohen, 1988, p. 477–478), the required sample size ranges from 36 to 106 for each experiment, depending on the power, which we vary from 0.5 to 0.95.

The study was conducted with undergraduate and graduate students, mostly with a background in finance. We carried out two sessions per experiment, each with approximately 30 to 40 students, in a controlled environment (laboratory with separate workplaces). Experiment 1 was also conducted online with additional participants. The total sample size is 108 for Experiment 1 and 71 for Experiment 2.

57 subjects were assigned to PF 1, 62 subjects to PF 2, and 60 subjects to PF 3. The average age of the sample is 23.9 years. Of the participants, 55.9% have a monthly income lower than CHF 1 000 and 36.3% have a monthly income between CHF 1 000 and 3 000. Most of the subjects

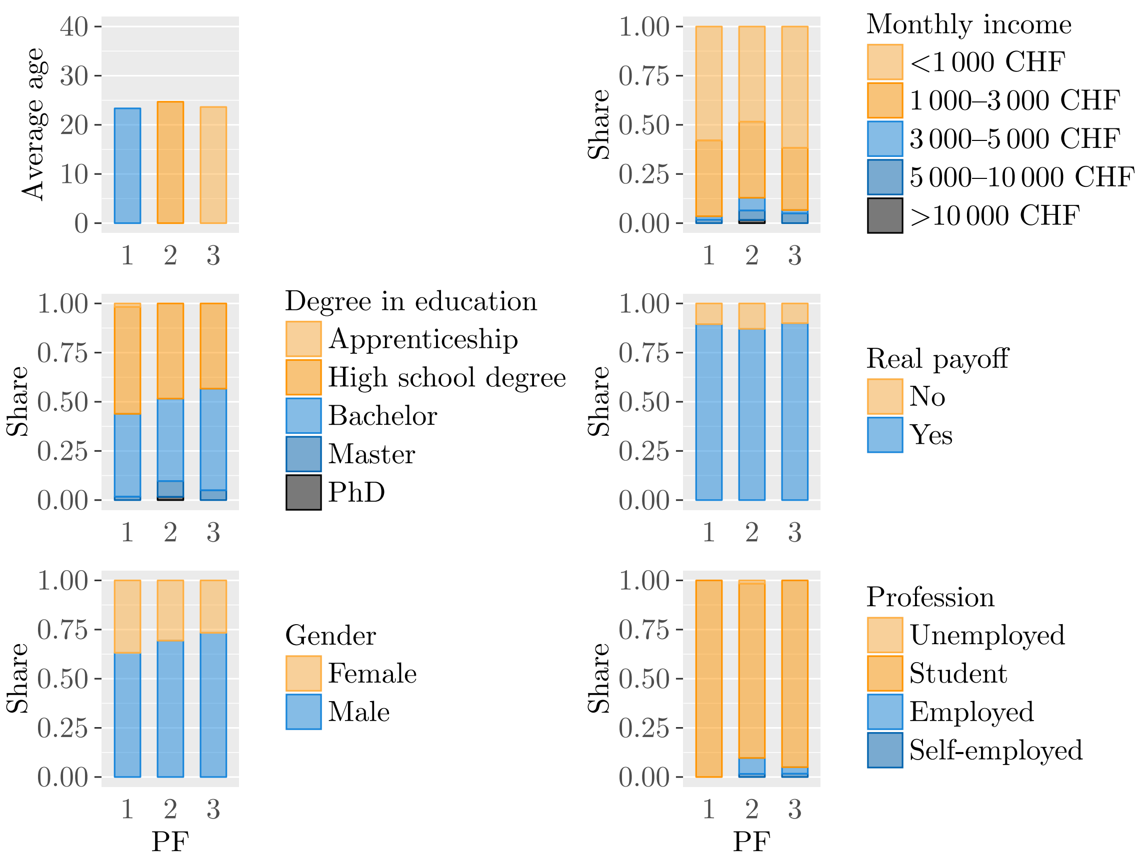


Figure 3.3.5: Demographical characteristics of the sample by PF groups

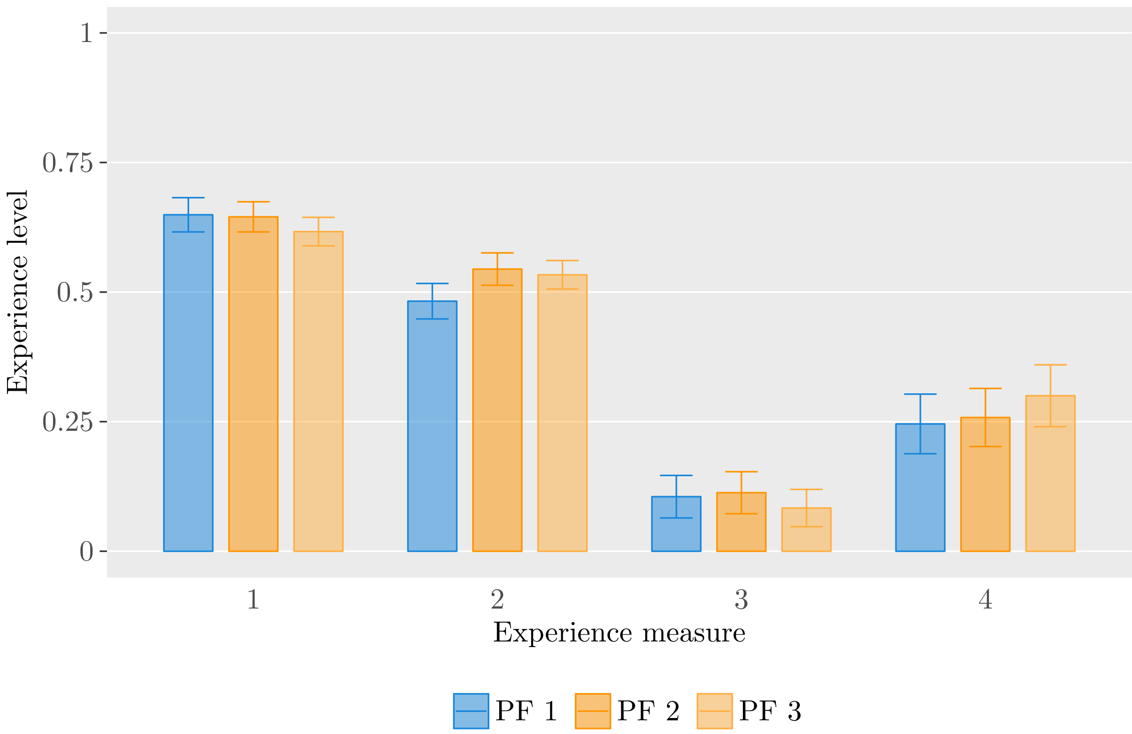


Figure 3.3.6: Level of (financial) experience. The graph compares the means and standard errors of different measures of subjects' investment experience across the three groups.

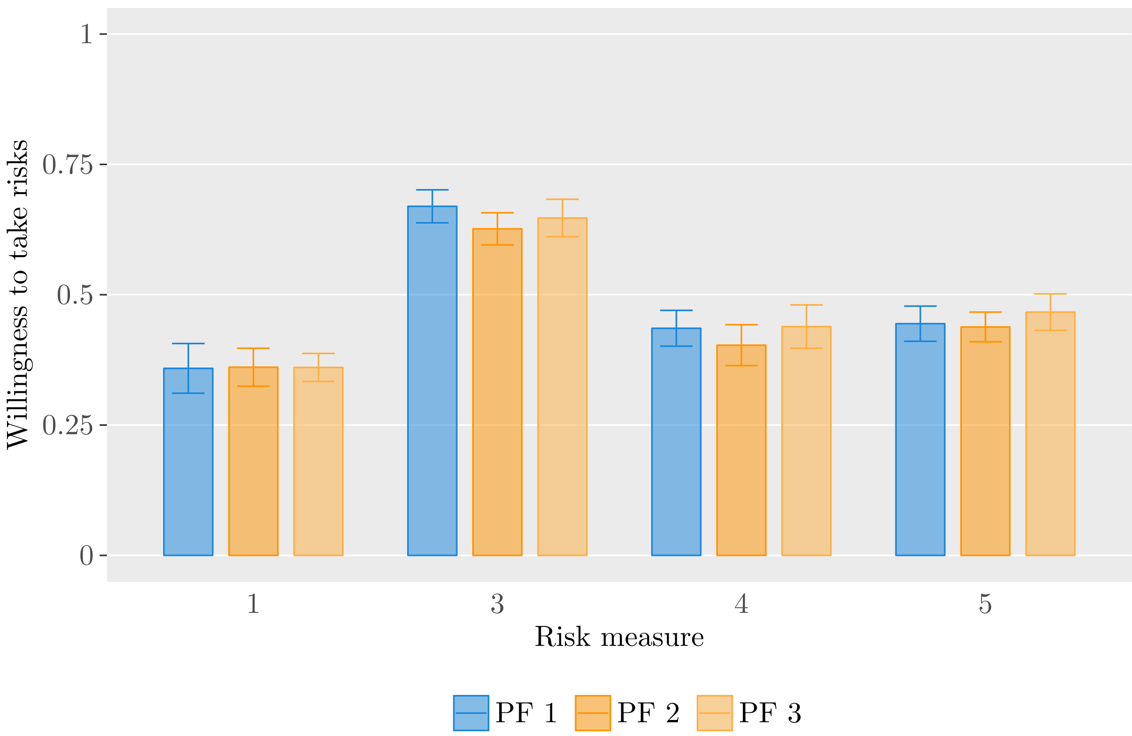


Figure 3.3.7: Willingness to take risks. The first two measures of subjects' risk preferences are based on certainty equivalents of lotteries with gains (risk preference measure 1) and losses (risk preference measure 2). The remaining three measures are derived from the DOSPERT scale of Blais and Weber (2006).

reported that their highest degree is either a high school diploma (48.6%) or a bachelor's degree (45.2%). 68.7% are male, 87.7% are Swiss citizens and 97.2% are unmarried. All subjects reported that they either have basic statistical knowledge (71.5%) or are very familiar with statistics (27.9%). Only a few subjects have never heard of structured financial products before (6.7%). A minority have invested in structured products (10.1%) or other assets (26.8%) before. The subjects are on average risk averse in the domain of gains and risk seeking in the domain of losses. Of the participants, 70.9% reported that it is likely that they will invest 10% of their annual income in a moderate growth diversified fund. However, only 37.5% (31.3%) indicated that they will likely invest 5% (10%) of their annual income in a very speculative stock (a new business venture).

Figure 3.3.5 shows the average values of different demographical variables for each group. The control group with PF 1 has a greater share of women than the other two groups (36.8% v. 30.6% and 26.7%). In addition, profession or rather income seems to be somewhat unevenly distributed. For instance, while there are only 48.4% with a monthly income below CHF 1 000 in the group with PF 2, the share in the other two groups is 57.9% and 55.9%, respectively. Apart from that, the groups are similar in terms of demographics.

Figure 3.3.6 and Figure 3.3.7 show the average outcomes and standard errors of the four experience measures and the five risk preference measures. To increase comparability, these measures were linearly transformed to a scale from 0 to 1. The risk preference measures are all defined in such a way that a higher value indicates a higher willingness to take risks.[20]

As can be seen in all three figures, the groups are relatively similar to one another. However, some measures reveal slight differences among groups, which are considered and canceled out in the statistical analysis.

3.3.6 Results

Attractiveness of Base Products

In the first investment choice, the participants evaluated the attractiveness of the three base products, i.e., the stock, CPP and RC. In the following, for ease of presentation, the attractiveness scores and other ordinal measures are transformed to a scale from 0 to 1. All statistics are

[20]For this reason, the risk preference measure 2 is defined as 1 minus the certainty equivalent for the lottery with losses.

based on these transformed variables.

Figure 3.3.8 shows the means and standard deviations of the attractiveness scores and investment weights for the three PFs. In Experiment 1 (upper panel), four observations stand out: 1) For the stock investment, the results are very similar across the PFs. 2) The results of PF 3 (fifty ordered payoffs) are similar to those of PF 1 (only payoff diagram). A natural explanation is that the structural aspects of the two graphs are similar (see Section 3.3.4). Apparently, the additional probability information embedded in PF 3 does not strongly affect the product assessments. 3) The ordering of the products is clear in PF 1 and PF 3: the CPP is perceived to be more attractive than the stock investment, and the stock investment is perceived to be more attractive than the RC. 4) PF 2 (probability histogram) has a substantial effect on the products' perceived attractiveness. From the point of view of participants who have access to the probability histograms, the CPP appears to be much less attractive and the RC much more attractive. As a result, the stock investment, CPP and RC all obtain roughly the same attractiveness score in PF 2.

In Experiment 2 (lower panel), the results for PF 1 and PF 3 are similar to Experiment 1. The only noteworthy difference is that the RC is regarded as more attractive when presented in PF 3 compared to PF 1. Owing to the higher interest rate, the expected stock return (interest rate + risk premium) is higher in Experiment 2 than in Experiment 1. This means that the maximum payoff of the RC is more likely, which is clearly visible in PF 3 but not in the payoff diagram PF 1. The additional probability information appears to be helpful in this case. The main difference between the results of Experiments 1 and 2, however, is that the CPP no longer loses its attractiveness when presented in PF 2. This is consistent with the notion that loss probability plays an important role in investment decisions. In the setting of Experiment 1, PF 2 highlights the large probability of losing 10% when investing in the CPP (bar shown in red), while in Experiment 2 no losses can occur so that all bars are shown in blue. We conclude that the additional information of PF 2 affects the perceived attractiveness of the CPP only if the protection level is below 100% so that a substantial loss probability becomes apparent.

These results are confirmed in a regression analysis (including control variables). Let A_i^p denote the attractiveness of product $p \in \{\text{stock, CPP, RC}\}$ from the perspective of subject i.

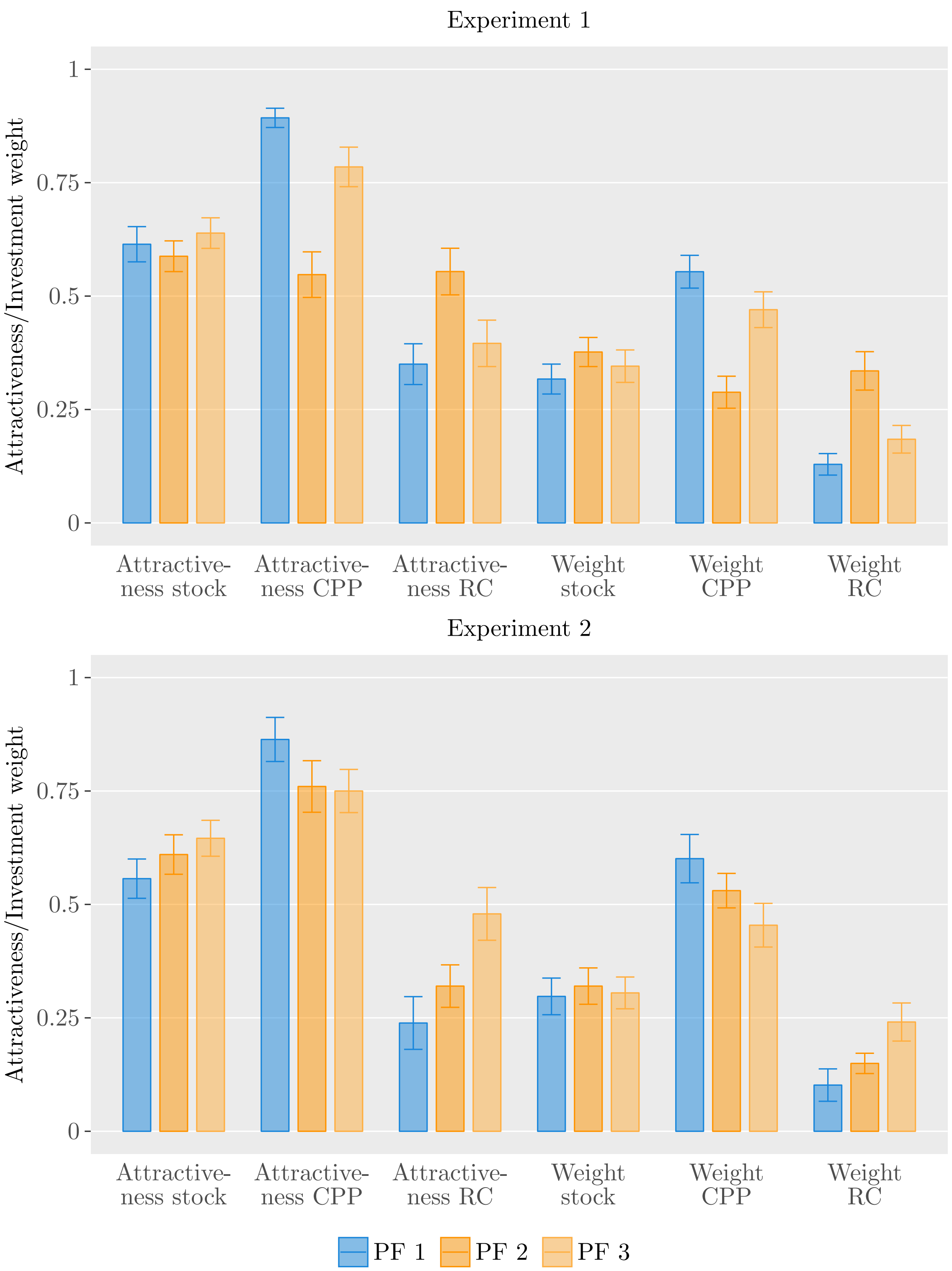


Figure 3.3.8: Perceived attractiveness and investment weights across the three presentation formats for study 1 (upper graph) and study 2 (lower graph)

For each p, we run separate regressions according to

$$A_i^p = \beta_0 + \beta_1 D_{i,PF2} + \beta_2 D_{i,PF3} + \beta_3 D_{i,PF1} D_{i,Exp2} + \beta_4 D_{i,PF2} D_{i,Exp2} + \beta_5 D_{i,PF3} D_{i,Exp2} + \gamma Z_i + \epsilon_i^p \tag{I}$$

$$\text{and } A_i^p = \beta_0 + \beta_1 D_{i,PF2} + \beta_2 D_{i,PF3} + \beta_3 D_{i,PF1} D_{i,Exp2} + \beta_4 D_{i,PF2} D_{i,Exp2} + \beta_5 D_{i,PF3} D_{i,Exp2} + \epsilon_i^p, \tag{II}$$

where β_0, ..., β_5 and the elements in vector γ are regression coefficients; Z_i is a vector of control variables; $D_{i,PF1}$, $D_{i,PF2}$ and $D_{i,PF3}$ are dummy variables that take on the value of 1 if subject i was exposed to PF 1, PF 2 or PF 3, regardless of whether the subject participated in Experiment 1 or 2; and $D_{i,Exp2}$ is a dummy variable that takes on the value of 1 if subject i participated in Experiment 2.

The intercept β_0 captures the base effect of PF 1 in Experiment 1 (minus the mean effect of the control variables). The coefficients β_1 and β_2 capture the additional effects of PF 2 and PF 3 in Experiment 1, respectively. Finally, the coefficient β_3 shows the additional effect of PF 2 in Experiment 2 compared to PF 2 in Experiment 1, and analogously for β_4 and β_5.

The first part of Table 3.3.1 shows the regression results. We run the same regressions with the dependent variable A_i^p replaced by the investment weight W_i^p attributed by subject i to product p. These results are shown in the second part of Table 3.3.1.

The table includes regression specifications with and without control variables. We find that the control variables do not have a strong impact on perceived attractiveness or the investment weights with the exception of three variables that are significant in at least some of the specifications. The first is a dummy variable that takes the value of 1 if participants collected their monetary compensation and is zero for the few participants who have not collected their gains. The subjects who received a real monetary payoff preferred the CPP more than the subjects who did not receive a real payoff. At the same time, the subjects invested less in the stock, which is the most risky investment option. This finding shows that subjects tend to invest more carefully when real money is at stake and supports the importance of monetary incentives in financial decisions. Second, men seem to have different preferences than women. For example, men perceive the RC to be more attractive. This result cannot be explained by the different risk preferences between men and women because the effect does not disappear when including risk preferences in the model and because the stock is riskier than the RC and is nonetheless rated

		Stock (I)	Stock (II)	CPP (I)	CPP (II)	RC (I)	RC (II)
Attractiveness	Intercept	0.31	0.61***	0.81**	0.89***	−0.24	0.35***
		(0.32)	(0.04)	(0.36)	(0.04)	(0.43)	(0.05)
	PF 2	−0.03	−0.03	−0.35***	−0.35***	0.20***	0.20***
		(0.05)	(0.05)	(0.06)	(0.06)	(0.07)	(0.07)
	PF 3	−0.02	0.02	−0.10	−0.11*	0.03	0.05
		(0.05)	(0.05)	(0.06)	(0.06)	(0.07)	(0.07)
	PF 1 × Exp. 2	−0.05	−0.06	−0.09	−0.03	−0.22*	−0.11
		(0.09)	(0.06)	(0.10)	(0.07)	(0.11)	(0.08)
	PF 2 × Exp. 2	0.01	0.02	0.16*	0.21***	−0.31***	−0.23***
		(0.08)	(0.05)	(0.10)	(0.06)	(0.11)	(0.07)
	PF 3 × Exp. 2	0.04	0.01	−0.06	−0.03	−0.03	0.08
		(0.09)	(0.06)	(0.10)	(0.07)	(0.12)	(0.07)
	Control variables	yes	no	yes	no	yes	no
	Observations	179	179	179	179	179	179
	R^2	0.11	0.02	0.34	0.19	0.25	0.12
	Adjusted R^2	−0.04	−0.01	0.22	0.17	0.11	0.09
	F Statistic	0.72	0.64	2.83***	8.36***	1.82**	4.59***
Investment weight	Intercept	0.31	0.32***	0.72**	0.55***	−0.03	0.13***
		(0.30)	(0.03)	(0.32)	(0.04)	(0.28)	(0.03)
	PF 2	0.05	0.06	−0.28***	−0.27***	0.23***	0.21***
		(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.04)
	PF 3	0.002	0.03	−0.07	−0.08	0.07	0.06
		(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.04)
	PF 1 × Exp. 2	−0.01	−0.02	0.01	0.05	−0.003	−0.03
		(0.08)	(0.05)	(0.08)	(0.06)	(0.07)	(0.05)
	PF 2 × Exp. 2	−0.03	−0.06	0.24***	0.24***	−0.21***	−0.19***
		(0.08)	(0.05)	(0.08)	(0.06)	(0.07)	(0.05)
	PF 3 × Exp. 2	−0.001	−0.04	−0.04	−0.02	0.04	0.06
		(0.08)	(0.05)	(0.09)	(0.06)	(0.08)	(0.05)
	Control variables	yes	no	yes	no	yes	no
	Observations	179	179	179	179	179	179
	R^2	0.16	0.02	0.38	0.18	0.30	0.16
	Adjusted R^2	0.005	−0.01	0.27	0.16	0.17	0.14
	F Statistic	1.03	0.71	3.47***	7.80***	2.38***	6.67***

*p<0.1; **p<0.05; ***p<0.01

Table 3.3.1: Regression analysis of perceived attractiveness and investment weights for the stock, the CPP and the RC

similarly. Third, risk preferences seem to have at least some importance. The subjects who are willing to pay a large amount to participate in a risky lottery with losses (risk preference measure 2) invest less in the CPP, which is consistent with the view that loss aversion leads to a preference for capital protection. However, surprisingly, there is no consistency among the five risk preference measures. When looking at the results, it is difficult to predict which product is preferred by risk-seeking or risk-averse individuals.

The most striking result in Experiment 1 apparent from Table 3.3.1 is that the CPP is very attractive for subjects in PF 1 and PF 3, while PF 2 makes the CPP appear much less attractive for the benefit of the RC (significantly negative PF 2 coefficients for the CPP and significantly positive PF 2 coefficients for the RC). However, these effects are not observed in Experiment 2 as the inverse signs of the coefficients for the interaction term PF 2 $\times$ Exp. 2 show. The attractiveness of the CPP is still smaller in PF 2 than in PF 1, but the difference is no longer significant.

Individual Structured Product Design

Figure 3.3.9 and Table 3.3.2 show the results of the second investment decision, where subjects had to design their own structured product. An overall observation is that the subjects limited the upside and downside potential but both at a large distance from the investment amount.[21]

In Experiment 1, as in the first investment decision, the choices of the PF 2 group deviate significantly from the other two groups. On average, the subjects from the second group chose a maximum payoff that is lower by CHF 1 433 when compared to the PF 1 group. In addition, their chosen minimum payoff is on average lower by CHF 585. This result is consistent with the finding in the first part that participants exposed to PF 2 find the capital protection feature less attractive and the RC characteristic more attractive than other participants. However, PF 2 does not seem to have a significant effect on the choice of the slope in the middle area. This coefficient is mostly above 1. As before, there is no significant difference between PF 1 and PF 3.

In Experiment 2, subjects chose a higher minimum payoff, which is consistent with the lower price of capital protection in this high-interest setting. The slope coefficient in PF 2 and PF 3 is close to one and therefore significantly smaller than in Experiment 1. A natural explanation

[21] The shape is similar to the average product resulting from the structured product design tool in Rieger and Hens (2012). The capital protection level, however, was higher in Rieger and Hens (2012) than in our study.

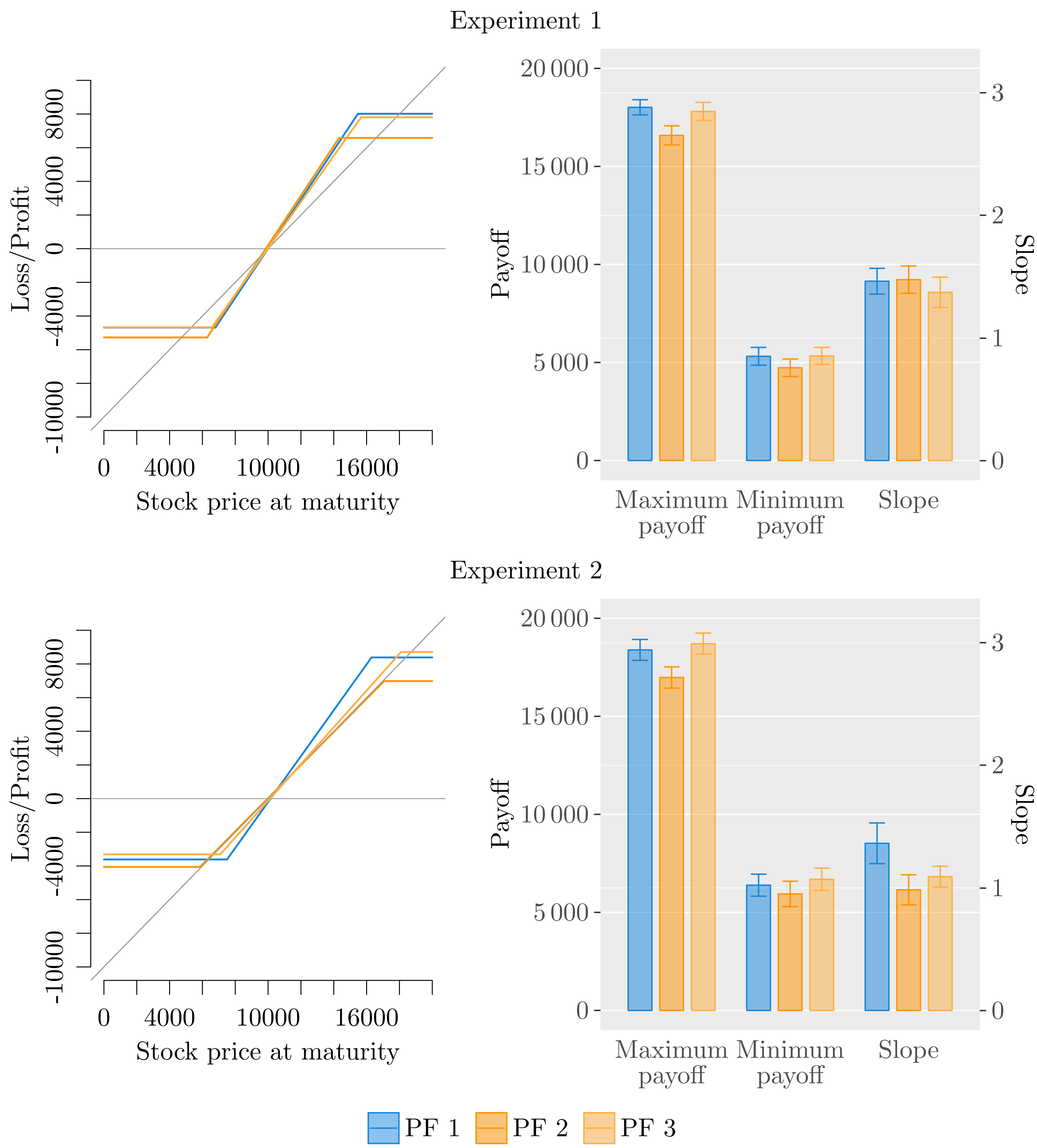


Figure 3.3.9: Properties of tailor-made structured products

is that subjects used a large slope in Experiment 1 to compensate for the low protection level, which is no longer necessary in Experiment 2.

There is some evidence that risk preferences play a role in the individual product design. Subjects who are likely to invest 5% of their annual income in a speculative stock (risk preference measure 4) chose a significantly lower minimum payoff. The other risk preference measures mostly indicate that a high willingness to take risks results in a preference for a low capital protection level, a low maximum payoff and a high slope, but the coefficients are not significant.

	Minimum payoff		Maximum payoff		Slope	
	(I)	(II)	(I)	(II)	(I)	(II)
Intercept	6 710	5 314***	11 738***	18 014***	−1.04	1.46***
	(4 057)	(467)	(3 963)	(450)	(0.97)	(0.11)
PF 2	−1 011	−585	−1 350**	−1 433**	0.02	0.01
	(666)	(652)	(650)	(628)	(0.16)	(0.15)
PF 3	277	19	3	−209	−0.13	−0.09
	(681)	(656)	(666)	(633)	(0.16)	(0.16)
PF 1 × Exp. 2	653	1 072	186	372	0.34	−0.10
	(1 079)	(752)	(1 054)	(725)	(0.26)	(0.18)
PF 2 × Exp. 2	666	1 210*	−403	399	0.03	−0.49***
	(1 064)	(715)	(1 039)	(690)	(0.25)	(0.17)
PF 3 × Exp. 2	233	1 354*	327	903	0.24	−0.28
	(1 104)	(728)	(1 079)	(702)	(0.26)	(0.17)
Control variables	yes	no	yes	no	yes	no
Observations	179	179	179	179	179	179
R^2	0.23	0.06	0.22	0.07	0.23	0.07
Adjusted R^2	0.09	0.03	0.08	0.05	0.10	0.05
F Statistic	1.65**	2.05*	1.60**	2.75**	1.71**	2.70**

*p<0.1; **p<0.05; ***p<0.01

Table 3.3.2: Regression analysis of the properties of tailor-made products

Interestingly, subjects who are familiar with structured products (experience measure 2) preferred products with a high maximum payoff. Other variables that seem to have an impact on the individual product design are age, gender and income. Older subjects chose a higher capital protection level. Men chose a significantly lower maximum payoff than women. Men's preference for a limited upside potential was already apparent in the first investment decision. Additionally, men chose a higher slope. Subjects with higher income tend to favor a high maximum payoff.

Reference Instrument

In the last part of the experiments, subjects compared the individually designed product with the volatility-adjusted combination of the stock and the risk-free asset. An important observation is that the results of Experiments 1 and 2 shown in Figure 3.3.10 and Table 3.3.3 are practically identical.

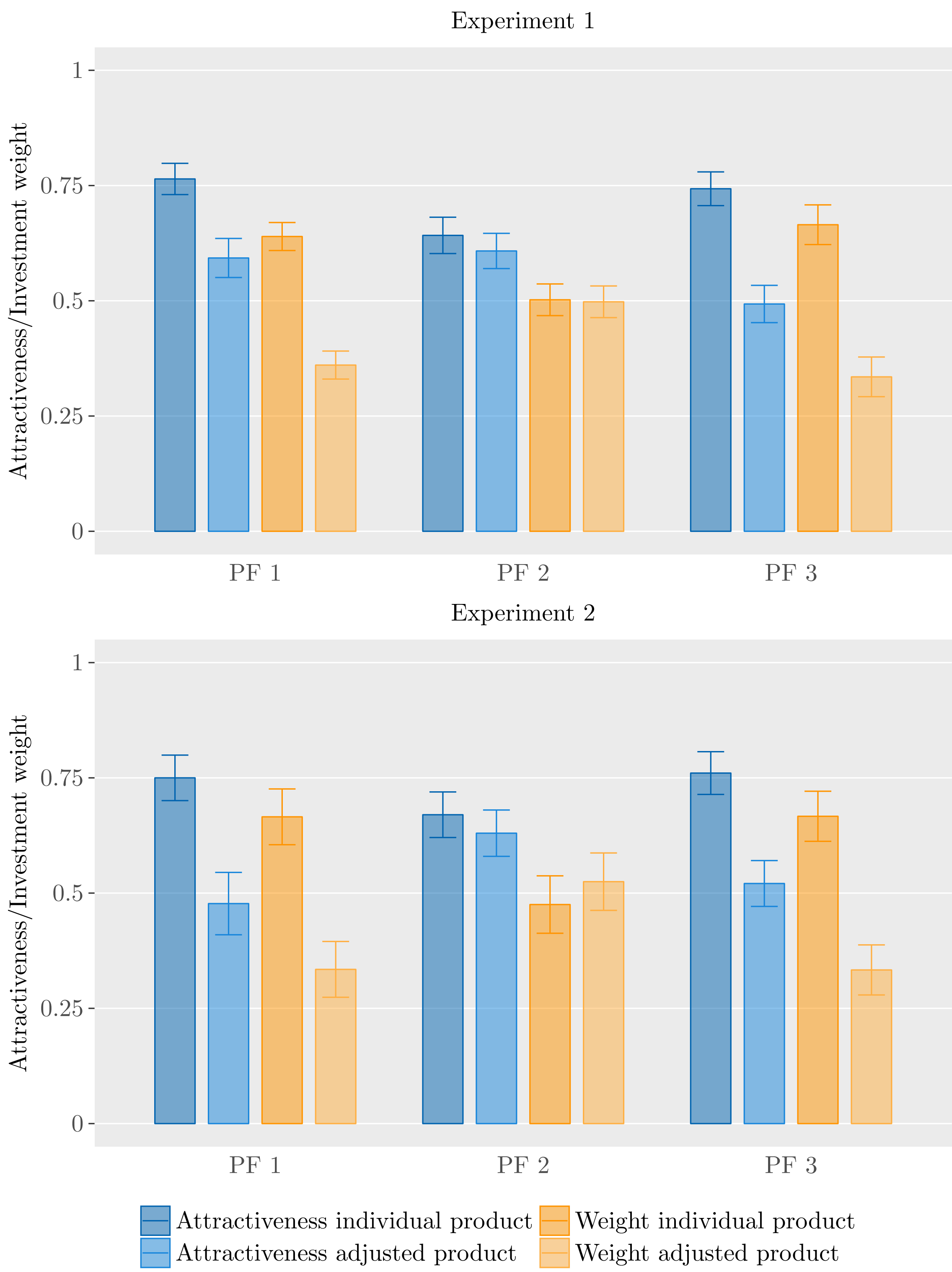


Figure 3.3.10: Perceived attractiveness and investment weights for the individual (tailor-made) and risk-adjusted product

		Experiment 1				Experiment 2			
Variable	PF	n	Mean	Sd	t-value	n	Mean	Sd	t-value
Delta attractiveness	1	35	0.17	0.35	2.88***	22	0.27	0.49	2.62**
Delta attractiveness	2	37	0.03	0.34	0.61	25	0.04	0.43	0.46
Delta attractiveness	3	36	0.25	0.41	3.70***	24	0.24	0.41	2.88***
Delta attractiveness	all	108	0.15	0.37	4.18***	71	0.18	0.45	3.38***
Delta investment weight	1	35	0.28	0.36	4.59***	22	0.33	0.57	2.73**
Delta investment weight	2	37	0.00	0.42	0.06	25	−0.05	0.62	−0.40
Delta investment weight	3	36	0.33	0.52	3.83***	24	0.33	0.53	3.07***
Delta investment weight	all	108	0.20	0.46	4.60***	71	0.20	0.60	2.79***

*p<0.1; **p<0.05; ***p<0.01

Table 3.3.3: Deviation between the attractiveness (or, alternatively, the investment weights) of individual (tailor-made) products and risk-adjusted reference instruments for different subject groups

In PF 1 and PF 3, the subjects perceived the individual product as more attractive. On average, they invested approximately 65% in the individual and only 35% in the volatility-adjusted product. In contrast, the PF 2 group did not show a preference for the tailor-made product on average, neither in the attractiveness score nor in the investment weights. Apparently, the simple linear product consisting of the stock and the risk-free asset is as attractive as the much more complicated structured product. This result suggests that the reference instrument is important, at least in the PF 2 mode, and it should be risk-adjusted to allow for a better comparison of the probability histograms.

The higher level of protection chosen in the high interest environment of Experiment 2 does not make subjects hold on to their individual product more strongly than in Experiment 1. The risk-adjustment of the alternative product takes the protection level into account, and the alternative product is also more attractive owing to the higher expected stock return. In both settings, PF 2 levels out the attractiveness of the individual and adjusted product.

It is important to note that it is the first moment of the distribution of the difference in attractiveness (delta attractiveness) and investment weights (delta weight) that shifts in PF 2. The second moment, however, is not systematically smaller in this PF, as can be seen from the standard deviations in Table 3.3.3. Thus, the individual preferences for one or the other product

		Individual product (I)	Individual product (II)	Adjusted product (I)	Adjusted product (II)	Delta (I)	Delta (II)
Attractiveness	Intercept	1.11***	0.76***	0.12	0.59***	0.99	0.17**
		(0.34)	(0.04)	(0.39)	(0.04)	(0.61)	(0.07)
	PF 2	−0.09*	−0.12**	0.03	0.02	−0.13	−0.14
		(0.06)	(0.05)	(0.06)	(0.06)	(0.10)	(0.09)
	PF 3	−0.02	−0.02	−0.11*	−0.10*	0.09	0.08
		(0.06)	(0.05)	(0.07)	(0.06)	(0.10)	(0.09)
	PF 1 × Exp. 2	0.01	−0.01	−0.09	−0.12*	0.11	0.10
		(0.09)	(0.06)	(0.10)	(0.07)	(0.16)	(0.11)
	PF 2 × Exp. 2	0.04	0.03	0.02	0.02	0.01	0.01
		(0.09)	(0.06)	(0.10)	(0.07)	(0.16)	(0.10)
	PF 3 × Exp. 2	0.05	0.02	0.04	0.03	0.01	−0.01
		(0.09)	(0.06)	(0.11)	(0.07)	(0.17)	(0.10)
	Control variables	yes	no	yes	no	yes	no
	Observations	179	179	179	179	179	179
	R^2	0.18	0.05	0.14	0.05	0.17	0.06
	Adjusted R^2	0.04	0.02	−0.02	0.02	0.02	0.03
	F Statistic	1.27	1.69	0.90	1.84	1.13	2.12*
Investment weight	Intercept	1.06***	0.64***	−0.06	0.36***	1.11	0.28***
		(0.38)	(0.04)	(0.38)	(0.04)	(0.76)	(0.08)
	PF 2	−0.12*	−0.14**	0.12*	0.14**	−0.24*	−0.27**
		(0.06)	(0.06)	(0.06)	(0.06)	(0.12)	(0.12)
	PF 3	0.03	0.03	−0.03	−0.03	0.06	0.05
		(0.06)	(0.06)	(0.06)	(0.06)	(0.13)	(0.12)
	PF 1 × Exp. 2	0.01	0.03	−0.01	−0.03	0.02	0.05
		(0.10)	(0.07)	(0.10)	(0.07)	(0.20)	(0.14)
	PF 2 × Exp. 2	−0.07	−0.03	0.07	0.03	−0.15	−0.05
		(0.10)	(0.06)	(0.10)	(0.06)	(0.20)	(0.13)
	PF 3 × Exp. 2	−0.02	0.002	0.02	−0.002	−0.05	0.003
		(0.10)	(0.07)	(0.10)	(0.07)	(0.21)	(0.13)
	Control variables	yes	no	yes	no	yes	no
	Observations	179	179	179	179	179	179
	R^2	0.20	0.10	0.20	0.10	0.20	0.10
	Adjusted R^2	0.06	0.07	0.06	0.07	0.06	0.07
	F Statistic	1.42*	3.74***	1.42*	3.74***	1.42*	3.74***

*p<0.1; **p<0.05; ***p<0.01

Table 3.3.4: Regression analysis of perceived attractiveness and investment weights for the individual (tailor-made) product and the risk-adjusted reference instrument

still appear to be strong in PF 2.

The results from the regression analysis in Table 3.3.4 suggest that education has an impact as well. Highly educated subjects seem to prefer the volatility-adjusted product more than less educated subjects.

3.3.7 Conclusion

There is an ongoing debate on how to present the risk and return characteristics of financial instruments in general and structured equity-linked products in particular. The large variety of structured products, their complexity and the non-linear payoff profiles make it difficult for investors to get a balanced view of risk and return. There is some evidence that behavioral biases play an important role in the success of structured products. The products are mostly illustrated with only a payoff diagram, and they are often compared to the underlying asset, although they are, by construction (limited downside or upside potential), less volatile. Information on the probability of possible outcomes appears to be crucial but is typically not provided. We argue that additional displays of outcome probabilities and risk-adjusted reference instruments can help to improve the correct assessment of risk and return of structured products. Thus, we propose different PFs for the probability distribution and test their effect on the perceived attractiveness of structured products.

Using a between-subject design for the PF, the participants rated the attractiveness of a stock, a CPP and a RC and took multiple investment decisions. In Experiment 1, the capital protection level was 90% while Experiment 2 assumed higher interest rates so that a protection level of 100% could be offered. Our results are consistent with the hypothesis that PFs that make the loss probability of the CPP clearly visible will lead to a downgrade of the product in Experiment 1 but not in Experiment 2. In this regard, bar charts with fifty ordered payoffs appear to convey only marginal probability information beyond payoff diagrams. Showing probability histograms, however, has a strong effect on the perceived attractiveness of structured products and leads to a much more critical assessment of the CPP in Experiment 1 but not in Experiment 2. This finding is consistent with prior literature on loss probability aversion, confirming that loss probability aversion plays an important role in investment decisions, and suggests that the presentation mode is important to reveal the loss probability.

When presenting probability histograms, we also find an important role of the reference instrument. In almost all graphical displays used in practice, the underlying asset is used as a reference instrument for comparison. We follow this practice when designing tailor-made products. When the individual product is then compared to a risk-adjusted linear instrument based on probability histograms, the participants no longer expressed a preference for one or the other. This result is the same in both experiments. Our interpretation is that participants who are confronted with probability histograms are more aware of the balance of risk and return in fairly priced products and less inclined to focus on individual aspects.

A limitation of our study is that we were not able to model both the PF and the reference instrument as between-subject variables. This would have required a subdivision of each group of subjects by reference instrument and a much larger sample size. Thus, our results on the reference instrument are indicative but inconclusive.

We also emphasize that our research design and results do not allow to conclusively answer the question whether and to what extent the display of outcome probabilities improves investment decisions. Given that subjects exhibit strong loss aversion also when provided with probability histograms, we argue that investment decisions are not necessarily improved in terms of a reduction of behavioral biases but rather in terms of an unbiased assessment of risk and return of financial products.

3.4 Myopic Loss Aversion and Structured Product Investments – The Impact of Evaluation Frequency on Risk-taking

3.4.1 Introduction

The question whether or not individuals should invest a larger portion of their capital in risky assets with increasing investment horizon is much discussed in practice. Some argue that above-average returns tend to offset below-average returns of stocks and the probability that the investment will result in a loss is relatively small over long investment periods. Others argue that the dispersion of the total investment return increases as the investment horizon expands. As a result, the magnitude of the potential loss is much larger compared to short-term investments.

Due to the normative nature of the above question, it may be difficult to provide investors with an universally acceptable recommendation. But the positive question whether or not individuals find risky investments more attractive when the investment horizon is long can be and has been tackled in an objective way. The literature dealing with this question is mostly inspired by Samuelson (1963). Samuelson offered one of his colleagues a simple coin flip bet, where he could either win USD 200 or loose USD 100. The colleague rejected the bet but was at the same time willing to accept it if it is played 100 times, a decision that is not rational under expected utility theory as Samuelson (1963) argued.

This behavior is often reflected in investment decisions, where it is referred to as myopic loss aversion (MLA). If the investment outcome is evaluated frequently (myopic behavior) and if the negative impact of losses is larger than the positive impact of equivalent gains (loss aversion, see Section 3.1.1), the experienced utility associated with owning stocks is low, given the relatively high loss probability of stock returns over short-term periods. The implication of this behavior on financial markets is that myopic investors tend to invest smaller amounts in risky assets, which potentially contributes to the paradoxically large underpricing of stocks compared to bonds known as the equity premium puzzle (Benartzi and Thaler, 1995).

Indeed, the above relation between the frequency of investment re-evaluations and the willingness to invest in risky assets has been confirmed in a multitude of experimental studies (see Section 3.4.2). In fact, some of these studies have been so influential that the view of MLA leading to decreased risk-taking has become very prevalent today. In my study, however, I argue that this relation does not always hold. Depending on the risk-return profile of the risky asset, myopia can even result in increased risk-taking. This was first pointed out by Langer and Weber (2005). The authors showed that under prospect theory there exist lotteries that are more attractive when played once rather than multiple times despite their positive expected payoff.

The goal of my paper is to test this finding in more realistic financial decisions using financial assets. In this regard, I analyze the attractiveness of stock indexes and RCs. The latter have a high probability of gaining a small profit and a small probability of suffering a relatively large loss and thus have similar risk and return characteristics as the lotteries in Langer and Weber (2005) that turned out to be less attractive when played multiple times. The effect of myopia on the attractiveness of RCs is particularly interesting since these products typically come with a relatively short time to maturity. Only few products are available with a term of many years. Due to the early expiration, investors are implicitly enforced to re-evaluate the investment outcome frequently.

I first analyze the attractiveness of these products over varying investment periods theoretically using cumulative prospect theory. The theoretical results are then compared to the outcome of a large-scale experiment, where subjects either took a long-term investment decision or multiple short-term investment decisions, in which they could invest in a stock index or a RC. According to prior studies suggesting that evaluation frequency reduces risk-taking, the expected outcome would be that the investment weights in both the stock index and the RC are lower for the subject group taking short-term decisions.

In addition to the evaluation frequency, my experiment has three other treatment variables. First, I varied the expected return of the stock index and the underlying asset of the RC to test whether my results are robust in different market phases. Second, I used varying investment horizons. These two treatment variables were included because the results of the theoretical analysis suggest that they are crucial factors for the effect of the evaluation frequency. Third, the subjects were further subdivided into three groups with different PFs. While the control group got no risk and return information, the other two groups obtained a histogram of either the aggregate, long-term return distribution or the segregate, short-term return distribution. The aggregation level of the risk and return information provided to decision makers was also found to be an important factor in the context of multiperiod investments (Redelmeier and Tversky, 1992; Benartzi and Thaler, 1999; Langer and Weber, 2001). The experimental study is thus primarily used to test whether frequent evaluations reduce the investment in assets with linear and nonlinear risk-return profiles and secondary to investigate the role of the market phase, investment horizon and the PF in this respect.

3.4.2 Literature Review

The notion of MLA was first introduced by Benartzi and Thaler (1995) as the combination of two behavioral concepts: loss aversion and the tendency of long-term investors to monitor their investments too frequently. The authors argued that the joint effect of these two concepts is a possible explanation of the well-known equity premium puzzle (see Mehra and Prescott, 1985). By analyzing the cumulative prospect theory utility of a bond portfolio and a stock portfolio over varying investment horizons, they found that bonds are more attractive for short-term investments and stocks are more attractive for long-term investments. The portfolios are equally attractive with a horizon of roughly one year.

The impact of the frequency of evaluations in investment decisions was also confirmed experimentally. Gneezy and Potters (1997) used a relatively simple experimental design, which has become the standard in testing the impact of MLA in the literature. The participants had to decide how much of their endowment they want to invest in a lottery, where they could either gain a return of 250% with a probability of 1/3 or suffer a loss of 100% with a probability of 2/3. The lottery was played for nine rounds. While one group played the rounds one by one (short evaluation period), the other group played the rounds in blocks of three and were informed about the aggregate results of three rounds (long evaluation period). It turned out that the average investment amount per round was significantly smaller for the high-frequncy group, supporting the theoretical analysis of Benartzi and Thaler (1995).

Thaler et al. (1997) conducted a similar study with two hypothetical funds. The funds differed greatly in terms of risk and return. Since no information was given to the subjects, they had to learn from experience about the risk involved in the products. The total investment period was 200 months. Depending on the treatment group to which the subjects had been assigned, they either made 200 decisions, 25 decisions (each of which was binding for 8 months), or 5 decisions (each of which was binding for 40 months). The average investment weight in the risky asset was significantly greater in the low-frequency groups, which shows that myopia has the same effect in investment decisions with financial assets as in investment decisions with lotteries.

Many variations of the groundbreaking experimental studies of Gneezy and Potters (1997) and Thaler et al. (1997) were published in the subsequent years. E.g., Gneezy et al. (2003) used an experimental setting with market interaction instead of individual decision-making. Haigh and List (2005) conducted experiments with professional traders. In the study of Eriksen and Kvaløy (2009), subjects found themselves in the role of an investment manager, in which they managed other people's money. The results reported in these publications are in line with the original studies from Gneezy and Potters (1997) and Thaler et al. (1997).

In most experiments, both the frequency of information feedback and the level of investment flexibility were manipulated simultaneously. It is thus unclear which of the two effects contributes more to the reduction in risk appetite. Bellemare et al. (2005), Langer and Weber (2008) and Fellner and Sutter (2009) addressed this question independently but provided contradicting answers. Bellemare et al. (2005) found that information feedback is the only driver, while the results of Langer and Weber (2008) suggest that investment flexibility is more important. Fellner and Sutter (2009), on the other hand, argued that both investment flexibility and feedback frequency are equally important (but there is no cumulative effect).

Dierkes et al. (2010) conducted a theoretical analysis of the attractiveness of different investment strategies over varying investment horizons under cumulative prospect theory. According to their results, bond (stock) portfolios are attractive in the short (long) term. A constant proportion portfolio insurance strategy turned out to be attractive for investment periods of roughly two to six years. A strategy with limited upside potential, as in the case of RCs, was not tested in their study.

In all of the above studies, the impact of myopia on risk-taking has proven to be very robust, contributing to the general consensus that frequent evaluations reduce investments in risky assets. This view was challenged by Langer and Weber (2005) and Beshears et al. (2017). Langer and Weber (2005) analyzed the attractiveness of different lotteries with two outcomes under prospect theory. Their results are in line with other studies for similar lotteries as used by Gneezy and Potters (1997). However, lotteries with a high gain probability but a small gain size and a low loss probability but a high loss size are more attractive when played once rather than multiple times. This is to some extent confirmed in the experimental study in the second part of the paper of Langer and Weber (2005), but the results are inconclusive owing to the relatively small number of participants and the lack of statistical power.

Beshears et al. (2017) run experiments with a more realistic investment environment in several respects. First, they used historical returns of existing assets. Second, the evaluation periods were dynamic, i.e., gains and losses of previous periods were transferred. Third, there were no (or only few) students in the sample. Fourth, they introduced a multiday delay between investment decisions and return realizations. The authors did not find any impact of myopia and argued that a higher evaluation frequency does not decrease risk-taking under these investment conditions. However, it is yet unclear whether the effect disappears completely or only declines slightly. In any case, these results show that a more thorough analysis of MLA is required to understand in which cases frequent evaluations lead to increased or decreased risk-taking.

Another crucial factor in the context of long-term investments is the aggregation level of risk and return information disclosed to investors. For instance, investors that are looking for long-term investment options but are provided with a distribution of returns over one year may favor low-risk assets due to the relatively large loss probability of stocks over short investment periods. The role of the aggregation level of risk and return information was examined in several studies. E.g., Redelmeier and Tversky (1992) analyzed the willingness to accept repeated lotteries in this context. They concluded that the attractiveness of risky assets increases when the aggregate distribution is known. Benartzi and Thaler (1999) and Beshears et al. (2017) complemented this study with an analysis of investment decisions with stocks and bonds, where either a short-term return distribution or a long-term, aggregate return distribution was provided to subjects, and yielded similar results. But again, this finding cannot be extended to assets with other risk and return characteristics, as Langer and Weber (2001) argued. Langer and Weber (2001) found that the segregate evaluation of lotteries with low probabilities for high losses and high probabilities for low gains leads to increased risk-taking.

The main contribution of my study to the existing literature on the impact of the investment evaluation frequency is the extension to investment decisions with nonlinear products. Furthermore, I analyze the impact of changes in the expected return of the risky asset and the PF of risk and return information within the scope of MLA, which has not been investigated in previous literature or only to a limited extend.

3.4.3 Attractiveness of Financial Products over Different Investment Periods under Cumulative Prospect Theory

I use cumulative prospect theory, as introduced by Tversky and Kahneman (1992), to analyze the attractiveness of financial products over different investment periods theoretically. In cumulative prospect theory, a decision maker evaluates a gamble with a set of negative outcomes $x_{-m}, ..., x_{-1}$ and positive outcomes $x_0, x_1, ..., x_n$ in ascending order and the corresponding probabilities $p_{-m}, ..., p_{-1}, p_0, p_1, ..., p_n$ by maximizing the utility function

$$V(x) = \sum_{i=-m}^{n} \pi_i v(x_i). \tag{3.7}$$

A value is assigned to each outcome according to the two-part power function of the form

$$v(x) = \begin{cases} x^{\alpha} & \text{if } x \geq 0, \\ -\lambda(-x)^{\beta} & \text{if } x < 0. \end{cases} \tag{3.8}$$

The decision weights are defined as

$$\pi_i = \begin{cases} w^{+}(p_i) & \text{for } i = n, \\ w^{+}(p_i + ... + p_n) - w^{+}(p_{i+1} + ... + p_n) & \text{for } 0 \leq i \leq n-1, \\ w^{-}(p_{-m} + ... + p_i) - w^{-}(p_{-m} + ... + p_{i-1}) & \text{for } -m+1 \leq i < 0, \\ w^{-}(p_i) & \text{for } i = -m, \end{cases} \tag{3.9}$$

with the probability weighting functions of the form

$$w^{+}(p) = \frac{p^{\gamma}}{[p^{\gamma} + (1-p)^{\gamma}]^{1/\gamma}}, \tag{3.10}$$

$$w^{-}(p) = \frac{p^{\delta}}{[p^{\delta} + (1-p)^{\delta}]^{1/\delta}}, \tag{3.11}$$

where α, β, δ, γ and λ are different parameters that represent the degree of loss aversion or diminishing sensitivity. For $\lambda > 1$, the value function in Eq. 3.8 features a greater sensitivity to losses than to gains. For $\alpha \in (0,1)$ and $\beta \in (0,1)$, the value function is less sensitive to changes of extreme outcomes. For $\gamma \in (0,1)$ and $\delta \in (0,1)$, the probability weighting functions in Eq. 3.10 and Eq. 3.11 is more sensitive to changes in probability near the end points. Due to the application of the cumulative probability distribution instead of the probability mass function, these values also result in an overweighting (underweighting) of extreme (middle) outcomes.

The new probability transformation approach is the main contribution of cumulative prospect theory in comparison to prospect theory because it prevents a violation of first-order stochastic dominance (Tversky and Kahneman, 1992).

Since the value of a structured product is based on its underlying asset, I first define the price process of the underlying asset. I assume a geometric Brownian motion with the annualized return μ and volatility σ in the following manner.

$$S_{i,t} = S_0 e^{\left(\mu - \frac{1}{2}\sigma^2\right)t + \sigma W_{i,t}} \tag{3.12}$$

$S_{i,t}$ are possible prices of the underlying asset at time t with an initial value of S_0. $W_{i,t}$ is a Brownian motion, i.e., it follows a normal distribution with mean 0 and variance t. Given the two parameters n and ΔZ and the sequence $(W_{i,t})_{i=-n}^{n}$ with $W_{i,t} = i\Delta Z\sqrt{t}$, the set of prices of the underlying asset at time t can be easily computed according to Eq. (3.12). The outcomes in prospect theory are, however, expressed in relative terms. For this reason, I compute the outcomes of the underlying stock for a given investment period T as

$$x_{i,T}^{S} = \frac{S_{i,T}}{S_0} - 1. \tag{3.13}$$

The corresponding probabilities can be obtained from the discretized probability density function of the geometric Brownian motion as follows.

$$p_{i,T} = \frac{1}{\sqrt{2\pi T} S_{i,T}\sigma} \exp\left[-\frac{\left(\ln S_{i,T} - \ln S_0 - \left(\mu - \frac{1}{2}\sigma^2\right)T\right)^2}{2\sigma^2} \right] \Delta Z \tag{3.14}$$

A very small ΔZ and a very large n is chosen such that the resulting set of outcomes and probabilities is sufficiently large to obtain a wide and smooth distribution of the underlying asset.

Based on the above results, I then determine outcomes of the RC. RCs with their limited upside potential can be decomposed into a long position of the underlying, a short call option (denoted by $-C_t$) and a long or short position in the risk-free asset. Thus, following the approach in Section 3.3.3 for the valuation of structured products, the product value of a RC at time $t = 0$ with maximum payoff M, term τ and strike price X of the short call option is defined as

$$RC_0 = S_0 - C_0(X) + (M - X)e^{-r\tau}. \tag{3.15}$$

I use the Black-Scholes option valuation model and set $RC_0 = S_0 = 1$. Then, the equation can be solved for X to obtain the strike price of a fairly priced RC. Afterwards, the set of possible outcomes at maturity is calculated as

$$\begin{aligned} RC_{i,\tau} &= S_{i,\tau} - C_\tau(X) + M - X \\ &= S_{i,\tau} - \max(S_{i,\tau} - X, 0) + M - X \\ &= \min(0, S_{i,\tau} - X) + M. \end{aligned} \tag{3.16}$$

The corresponding probabilities are the same as for the underlying stock if the investment period corresponds to the product's term, i.e., if $T = \tau$. I assume that all RCs have a term of one year (i.e., $\tau = 1$). This term is indeed very common, in particular for (barrier) reverse convertibles. Given an investment horizon of multiple years, the investor would need to reinvest the initial budget plus the proceeds of past years in a newly issued, similar product after every expiration day. I mimic this practice with a simulation approach by drawing T outcomes for $RC_{i,\tau}$ for each simulation path j, with τ being a factor of T, and calculating the final wealth as

$$RC_{j,\tau,T} = \frac{RC_{1,\tau}}{RC_0} \cdot \frac{RC_{2,\tau}}{RC_0} \cdot \ldots \cdot \frac{RC_{t,\tau}}{RC_0} = \frac{\prod_{i=1}^{T} RC_{i,\tau}}{RC_0^T} \tag{3.17}$$

and the relative outcomes as

$$x^{RC}_{j,\tau,T} = \frac{RC_{j,\tau,T}}{RC_0} - 1. \tag{3.18}$$

The outcomes $x^{RC}_{j,\tau,T}$ are identically distributed, whereas each outcome has a probability of 1 divided by the number of simulation paths.

I conduct the analysis for different investment horizons and specifications of the underlying stock and RC, namely $T \in \{1, \ldots, 10\}$, $\mu \in \{5\%, 10\%, 15\%\}$, $\sigma \in \{10\%, 20\%, 30\%\}$ and $M \in \{103\%, 110\%\}$. Alternative values for μ and σ represent different market phases. For the cumulative prospect theory parameters, I take the median estimates from Tversky and Kahneman (1992), i.e., $\alpha = \beta = 0.88$, $\gamma = 0.61$, $\delta = 0.69$ and $\lambda = 2.25$. I also assume a zero risk-free interest rate independent of the investment period.

The resulting utilities are plotted in Figure 3.4.1. In the long term, the stock is the most attractive investment option, followed by the RC with a maximum payoff of 110%. The ranking is less consistent for short-term investment horizons, where either the stock or risk-free asset is preferred, depending on the choice of μ and σ. RCs are either located between these two options or yield a lower utility.

The primary focus of this study is, however, the slope of the products' utility as a function of the investment period. In line with numerous other studies on MLA (see Section 3.4.2), I find a positive slope for the stock in all settings; i.e., the attractiveness of the stock increases with the length of the investment period. Based on this theoretical finding, I formulate the first hypothesis for the experimental study.

H1 *Frequent evaluations lead to decreased risk-taking for investments in stocks.*

In most cases, this finding also holds for RCs. However, when comparing the attractiveness of these products over short- and mid-term investment horizons in stagnating and volatile market phases, my theoretical results predict a decreasing utility with increasing investment horizon. I

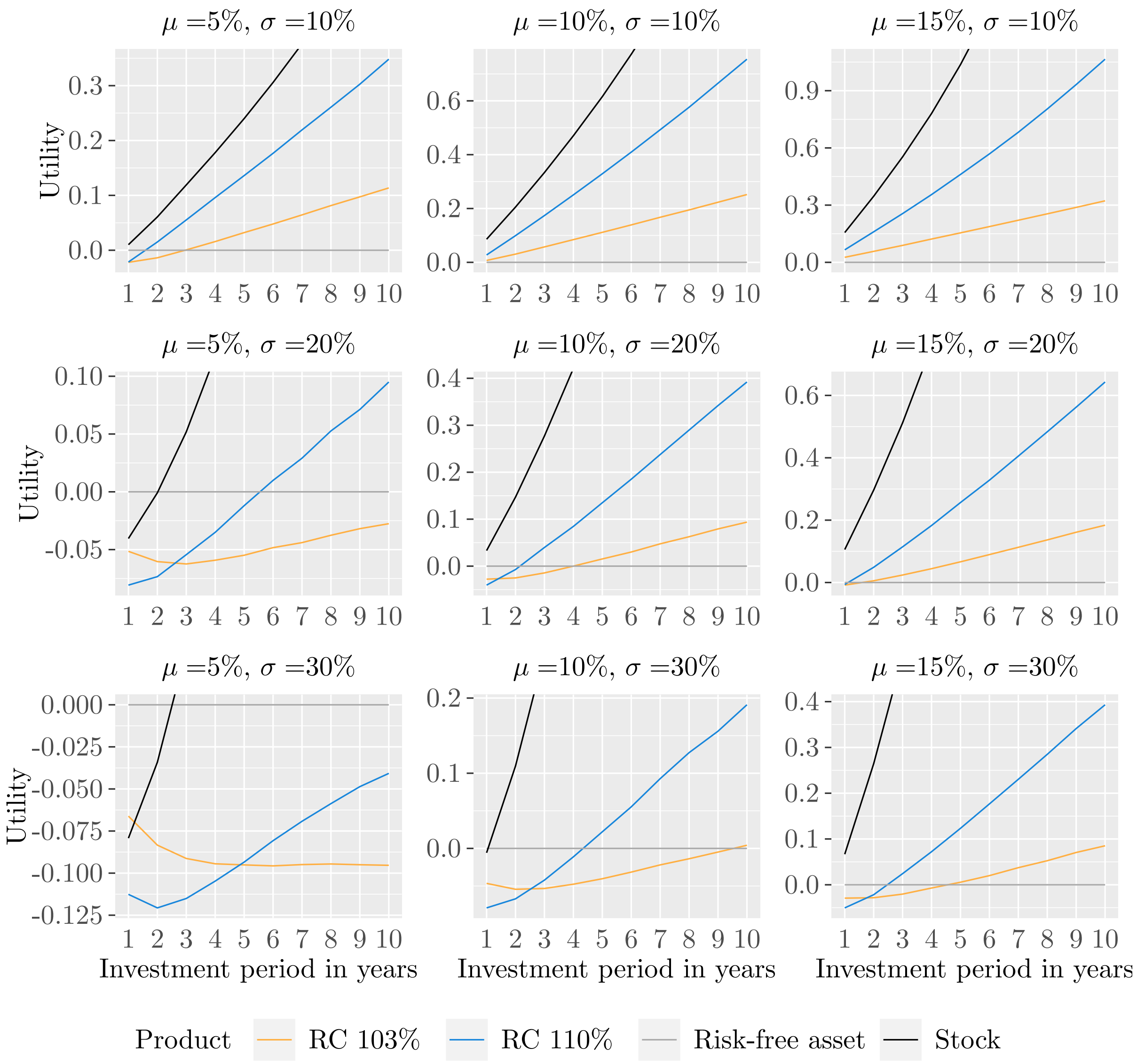


Figure 3.4.1: Cumulative prospect theory utility of various structured and non-structured products in different market phases

thus hypothesize the following.

H2a *Frequent evaluations lead to increased risk-taking for investments in RCs over short- and mid-term investment horizons in stagnating and volatile market phases.*

This is particularly true for the RC with low maximum profit. In the long term, the utility starts to increase again and exceeds the initial utility level in most settings. Also, the graphs show a monotonically increasing utility for investments in RCs when the mean return of the underlying is high and its volatility low. The following hypothesis is predicated on these findings.

H2b *Frequent evaluations lead to decreased risk-taking for investments in RCs over long-term investment horizons in upward trending and stable market phases.*

3.4.4 Experimental Design

My experimental design builds on previous studies on MLA. The subjects were faced with investment decisions for a given investment horizon. They started with a hypothetical investment budget of GBP 10 000, which could be either invested in a given risky asset or retained. The retained proportion yielded no profit and no loss. The risky asset offered for investment was either a stock index or a RC. This treatment variable was implemented as within-subject variable. Thus, each subject took the investment decisions with the stock index and the RC successively. The order was determined randomly.

To not bias the results towards prevalent views, I did not name a specific stock index and only indicated that it consists of a large number of individual companies from developed countries. Accounting for the results of the theoretical analysis, I chose a RC with a maximum payoff of 103% of the invested capital. The choice of these two investment options allows for a confirmation of the results of prior experimental studies on MLA and a disproof of the universal validity of the predominant view that a high evaluation frequency reduces risk-taking using the same subject pool, at least when it comes to the theoretical analysis.

To test the impact of the evaluation frequency, the subjects either evaluated their investment and reallocated the investment weights on a yearly basis (high evaluation frequency) or made investment decisions only once for the entire investment period without any possibility to adapt the investment weights (low evaluation frequency). In the high-frequency decisions, prior gains and losses were carried over as in realistic investment decisions and the investment budget was adapted in every sub-period.

	Mean return of the stock index/ underlying (μ)	Investment horizon (T)
Setting 1	5% p.a.	3 years
Setting 2	10% p.a.	3 years
Setting 3	5% p.a.	10 years
Setting 4	10% p.a.	10 years

Table 3.4.1: Overview of experimental settings

As pointed out in the theoretical analysis, the evaluation frequency can have contrary effects on the attractiveness of the RC, depending on the length of the total investment horizon and market conditions. For this reason, I further manipulated these two factors by conducting the experiment in four different settings. In setting 1, I assumed a mean return of the underlying of 5% p.a. and an investment horizon of 3 years. In setting 2, the investment horizon was the same but the mean return was 10%. In setting 3, the mean return amounted to 5% again but the investment horizon was 10 years. In setting 4, I applied a mean return of 10% and an investment horizon of 10 years. An overview is given in Table 3.4.1. In all settings, a return volatility of the underlying of 20% is assumed, which roughly corresponds to the long-term level of large stock indexes. Based on the theoretical results, I expect increased investment amounts for the RC in high-frequency decisions in setting 1 (H2a) but not in settings 2, 3 and 4 (H2b).

Another important manipulation is the PF or, more concretely, the aggregation level of the risk and return information provided to subjects. A part of the subjects obtained risk and return information over a short-term investment horizon; i.e., probabilities of yearly returns of the risky asset were displayed, irrespective of whether the subject took short-term, high-frequency or long-term, aggregate decisions. Another part of the subjects got risk and return information whose aggregation level was aligned with the feedback frequency. Thus, if a subject took short-term decisions on a yearly basis, he/she got probabilities of yearly returns, and if a subject took long-term decisions, he/she got probabilities of returns over the total investment horizon. The probability information was always displayed in form of a histogram. Figure 3.4.2 shows histograms of returns over 1 year and 3 years for both the stock index and RC as used in setting 1. Histograms used in other settings can be found in Appendix C.1. The last part of the subjects got no probability information at all. Only a payoff profile of the RC was provided

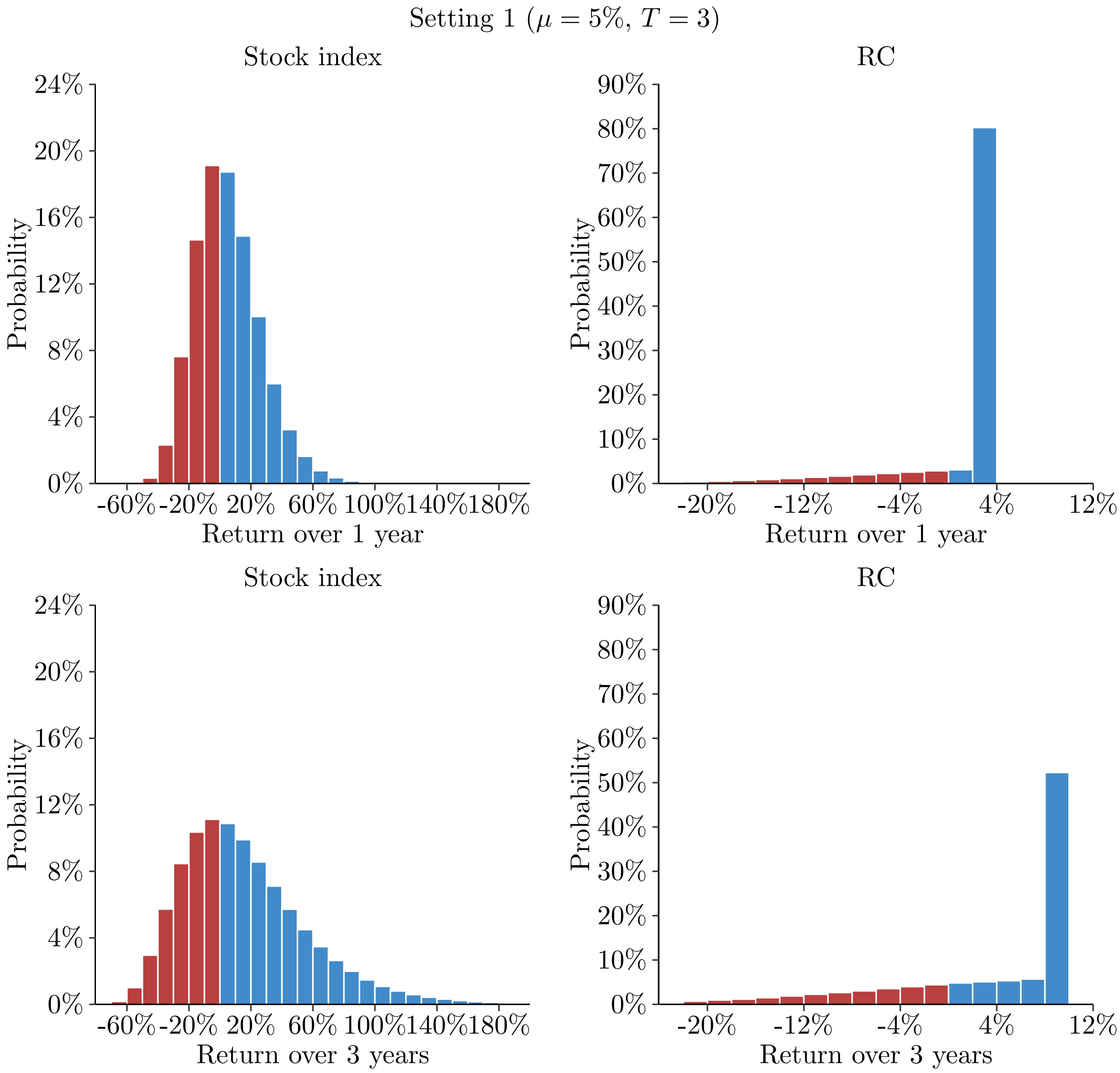


Figure 3.4.2: Histograms of returns over 1 year (top) and 3 years (bottom) for the stock index (left) and RC (right) in setting 1

to improve the understanding of the product. This approach corresponds to general practice to present structured products.

Previous literature suggests that investors are more risk-seeking when the aggregate distribution of stock returns is known (see Section 3.4.2). While there are no such studies for RCs, I believe that in any case the disclosure of probability information helps to make investment decisions that are in line with the investors' preferences for a given investment horizon. Accordingly, I expect that the provision of risk and return information with aligned aggregation level leads to results in line with cumulative prospect theory, while for the other two PFs the difference in attractiveness of a given risky asset over short- versus long-term investment periods is less

Treatment variable	Design	Levels
Investment option	Within-subject	Stock index or RC with 103% maximum payoff
Evaluation frequency	Between-subject	Yearly (high frequency) or one evaluation for the entire investment horizon (low frequency)
Risk and return information	Between-subject	No information, short-term information or aligned aggregation level
Investment horizon (T)	Between-subject	3 years (settings 1 and 2) or 10 years (settings 3 and 4)
Mean return of the stock index/underlying (μ)	Between-subject	5% (settings 1 and 3) or 10% (settings 2 and 4)

Table 3.4.2: Overview of treatment variables

obvious. This leads us to my last hypothesis as follows.

H3 *The effect of the evaluation frequency is more pronounced if risk and return information with aligned aggregation level is provided.*

Table 3.4.2 gives an overview of all treatment variables used in the experiment. Overall, it is a $2 \times 2 \times 3 \times 2 \times 2$ mixed experimental design with 20 subject groups[22]. The PF and evaluation frequency were assigned randomly to subjects. Experiments with different experimental settings were conducted successively (i.e., I started with setting 1, continued with setting 2 etc.).

The investment decisions were taken in the first two stages of the experiment (one stage for the stock index and one stage for the RC). Each investment stage was initiated with an introduction of the respective risky asset including the associated risk and return information. The subjects then took either multiple short-term investment decisions or one long-term investment decision. After every short-term decision, subjects received feedback on the outcome of the last investment decision and were informed about the height of the adapted investment budget for the next decision. After the last short-term decision or the long-term investment decision, respectively, they (also) got feedback on the overall performance in the respective stage. The investment stages were terminated with a test question to control whether the participants

[22]In high-frequency investment decisions, the groups with aligned risk and return information received the same probability information as the groups with short-term information. For this reason, the total number of groups is reduced by 4 groups (one group per setting).

understood the product. The test question on the stock index included four true or false statements. These statements basically predicated that an investment in the stock index can or cannot yield a return or suffer a loss of a certain percentage within the specified investment horizon. Knowing that the profit is unlimited and that the loss is limited to the invested capital, which was explicitly indicated in the introduction of the asset and implicitly suggested by the risk and return information, the subjects could easily pass this test question. The test question on the RC asked for the maximum possible profit when investing in the product for one year. Subjects had to choose the correct answer "3%" out of five given answers. In a similar manner as for the stock index, the correct answer was given in the product introduction and return histograms.

To control for differences in subject groups, the investment stages were followed by various questions, which are very similar to those in the study in Section 3.3.4. First, the experience in financial decisions was tested with four different measures. I asked the subjects whether they are familiar with statistics, whether they are familiar with structured products, whether they have already invested in stocks, mutual funds or bonds, and whether they have already invested in derivatives or structured products. Second, I tried to elicit risk preferences using six different measures. One general question was how the subjects would assess their risk attitude in financial decisions on a five-step scale. Then, I asked more concretely how likely it is on a seven-step scale that they would invest a certain percentage of their annual income in either a moderate growth diversified fund, a speculative stock or a new business venture. These three measures (one measure per investment option) were taken from the domain-specific risk-taking (DOSPERT) scale of Blais and Weber (2006). The last two measures were certainty equivalents for two different lotteries derived from Rieger et al. (2014). Finally, I asked the subjects for demographic information including gender, age, marital status, place of residence, education, employment status and income.

I also incentivised subjects with a bonus, which they received on top of a small fixed compensation of GBP 1. The bonus payoff corresponds to the percentage return gained/lost at one of the two investment stages applied to the base amount of GBP 2. The investment stage was picked randomly at the end of the experiment. To further improve the quality of the responses, the participants only received the bonus payment if the control questions were answered correctly.

Appendix C.2 provides an overview of the variables used in the study. Appendix C.3 includes screenshots of the experiment.

3.4.5 Participants

The experiment was conducted online. Subjects were recruited through the platform Prolific[23]. 2 470 subjects in total participated in the experiment. The experimental settings 1, 2, 3 and 4 include 616, 581, 599 and 674 subjects respectively. 1 546 subjects took low frequency, long-term decisions and only 924 subjects took high-frequency, short-term decisions. The reason for the unequal allocation is that the PF for short-term decisions was identical for the short-term information and aligned information subject groups such that there was no need to collect the same data twice. 1 122 subjects received no probability information, 896 subjects received short-term information and 888 subjects received aligned information (including 436 subjects with short-term information).

Most subjects (52.6%) have a monthly net income between GBP 1 000 and 3 000. They are mostly well-educated with 95.4% of the sample having at least a bachelor degree. 35.6% hold at least a master degree and 4.7% have a PhD. The reason for the high educational background is that I used it as criteria to filter potential participants due to the relatively complex tasks in the experiment. In terms of gender, the sample is evenly split with 50.9% being female and 49.1% being male. Most of the subjects are either employed (67.1%), student (11.8%) or self-employed (10.3%) and some of them are unemployed (8.0%) or retired (2.8%). The subjects' residence is mostly located in Europe (74.7%) or North America (21.9%). Some participants are from Oceania (1.3%). The weight of other geographical regions (Africa, Asia, Middle East, South and Central America) in the sample is negligible. On average, a subject is 34 years old.

In terms of financial knowledge, many subjects indicated that they either have basic (51.2%) or advanced knowledge (10.1%) about financial assets. Also, many of them have at least some knowledge about derivatives or structured financial products (40.6%). More importantly, a relatively high proportion of subjects has already invested in stocks, funds or bonds (46.0%) and a considerable number of subjects has already invested in derivatives or structured products (12.3%). The participants also indicated that their general risk attitude in financial decisions

[23]While Amazon's crowdworking platform Mechanical Turk is mostly used to recruit participants for online experiments, the new, alternative platform Prolic is getting increasing attention as it is explicitly targeted at researchers. See Palan and Schitter (2018) for a discussion on the suitability of Prolific for recruiting subjects.

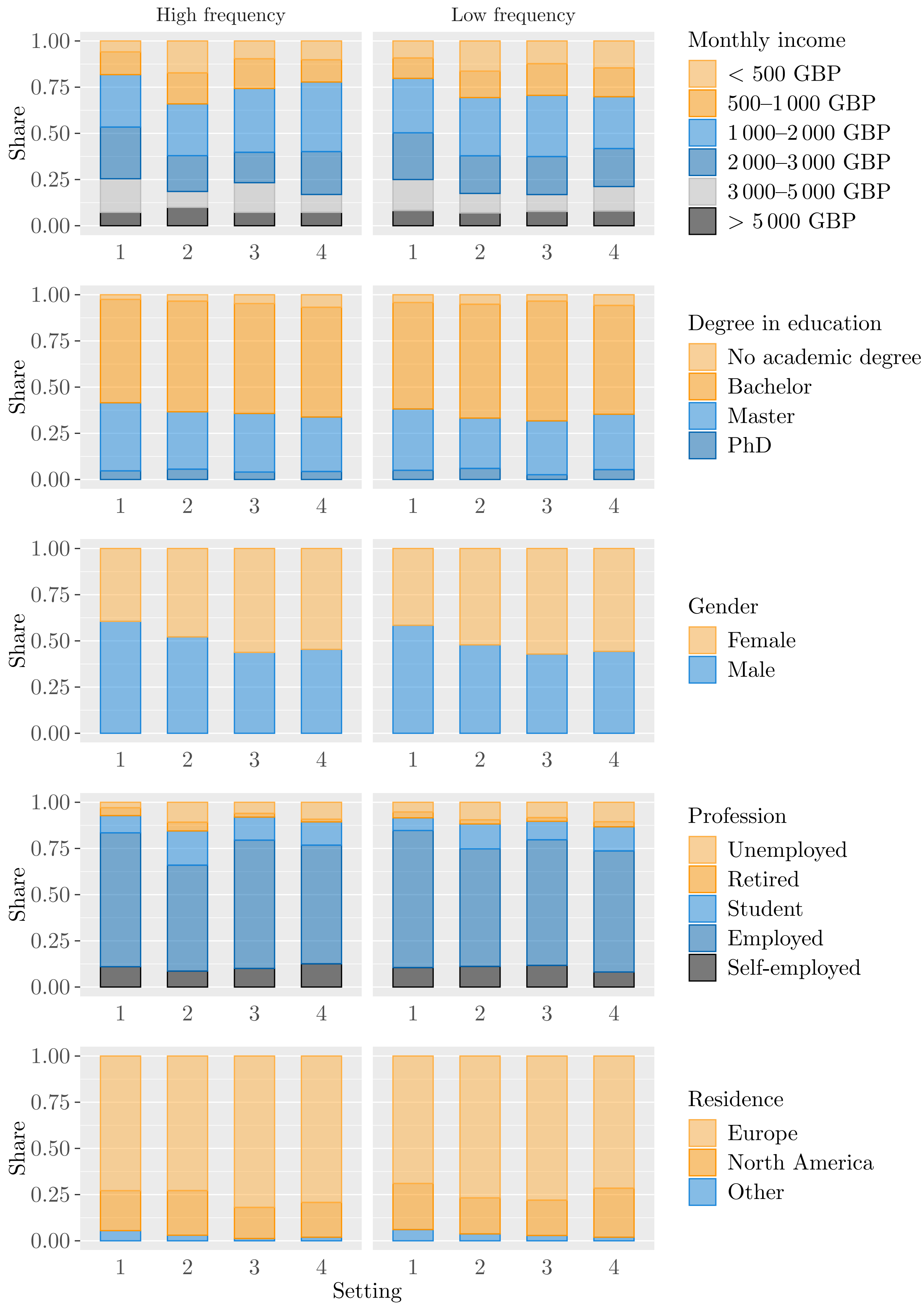


Figure 3.4.3: Categorical demographical characteristics of the subjects with high evaluation frequency (left) and low evaluation frequency (right) subdivided by experimental setting (horizontal axis)

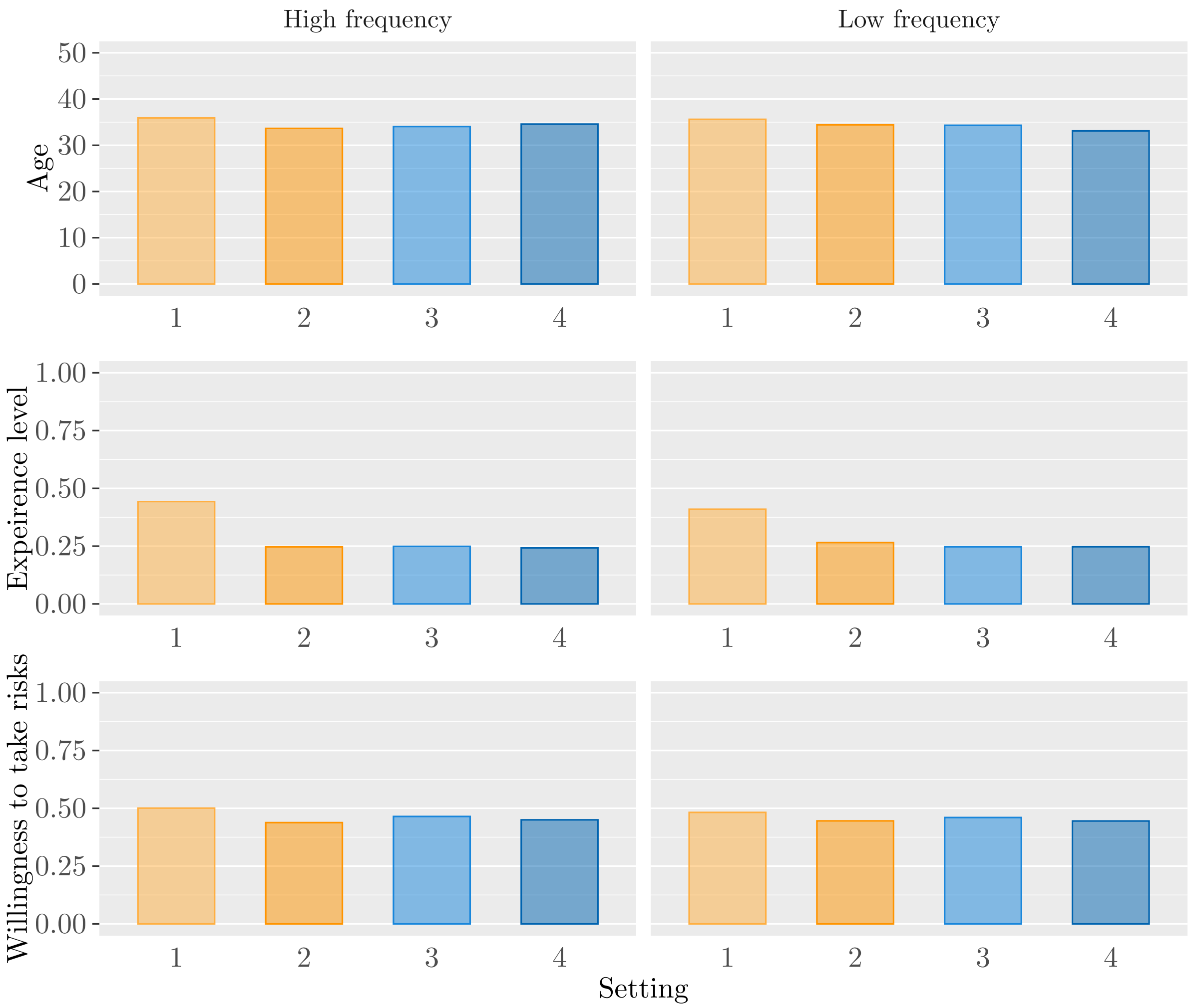


Figure 3.4.4: Average age, financial experience level and willingness to take risks of the subjects with high evaluation frequency (left) and low evaluation frequency (right) subdivided by experimental setting (horizontal axis)

is either very conservative (17.8%), conservative (35.5%), moderate (33.8%), aggressive (11.1%) or very aggressive (1.7%). Overall, this sample is well-suited for a study on financial decisions compared to a student sample given the high level of investment experience, income and thus probably also wealth to invest.

Figures 3.4.3 and 3.4.4 give an overview of demographical and other characteristics of the sample and compare different subject groups in terms of these characteristics. The experience level and willingness to take risks are combined measures corresponding to an average of quantified answers to multiple questions (see Section 3.4.4 for more details). The answers are transformed linearly on a scale from 0 to 1.

When comparing the subject groups subdivided by evaluation frequency and experimental setting, one can observe a relatively high level of homogeneity with respect to all characteristics.

Only the experience level seems to be higher in setting 1 than in other settings. The reason behind that is a filter used in the first setting allowing only for participants with prior investment experience. This filter was no longer used in the other settings because the number of potential participants would have been too low (to conduct the experiment in a reasonable time). This filter may have also caused other small differences between the subject groups, such as income (which is slightly higher in setting 1) and gender distribution (the share of men is larger in setting 1). There are, however, no significant differences when comparing high frequency with low frequency subject groups, which is the primary concern of this study, such that I do not expect biased results on the impact of the evaluation frequency. Nonetheless, I account for these differences by adding control variables on the subjects' characteristics in the statistical analysis.

3.4.6 Results

Figure 3.4.5 shows the average investment weights and standard errors of different subject groups for both products (stock index and RC) and in all experimental settings. The average investment weight for the stock varies between roughly 35% and 55% depending on the setting, evaluation frequency and PF. Surprisingly, the stock index seems to be most attractive if no risk information is displayed in the majority of cases. A possible explanation is that the stock index does indeed have an unattractive risk-return ratio, which gets apparent with the histograms provided to the short-term and aligned information subject groups. The difference in mean investment weights between different PF groups is more pronounced in settings 1 and 3, where the mean yearly return of the stock index is only 5%. In settings 2 and 4, where the mean return is 10% p.a., the difference disappears (at least in high-frequency decisions). For the RC, the average investment weights are very roughly at the same level as for the stock index (between 35% and 55%), but the PF has exactly the opposite effect. While the investment weights are generally low when no risk and return information is provided, the product is perceived to be relatively attractive especially when short-term information is displayed. These results are in line with the study on the impact of the PF on the perceived attractiveness of structured products in Section 3.3.

To analyze the impact of the mean return of the stock index/underlying on average investment weights, I compare the results in setting 1 (5% p.a.) to the results in setting 2 (10% p.a.) and the results in setting 3 (5% p.a.) to the results in setting 4 (10% p.a.). Given the higher attractiveness of both products in the settings 2 and 4, I expect greater investment weights in

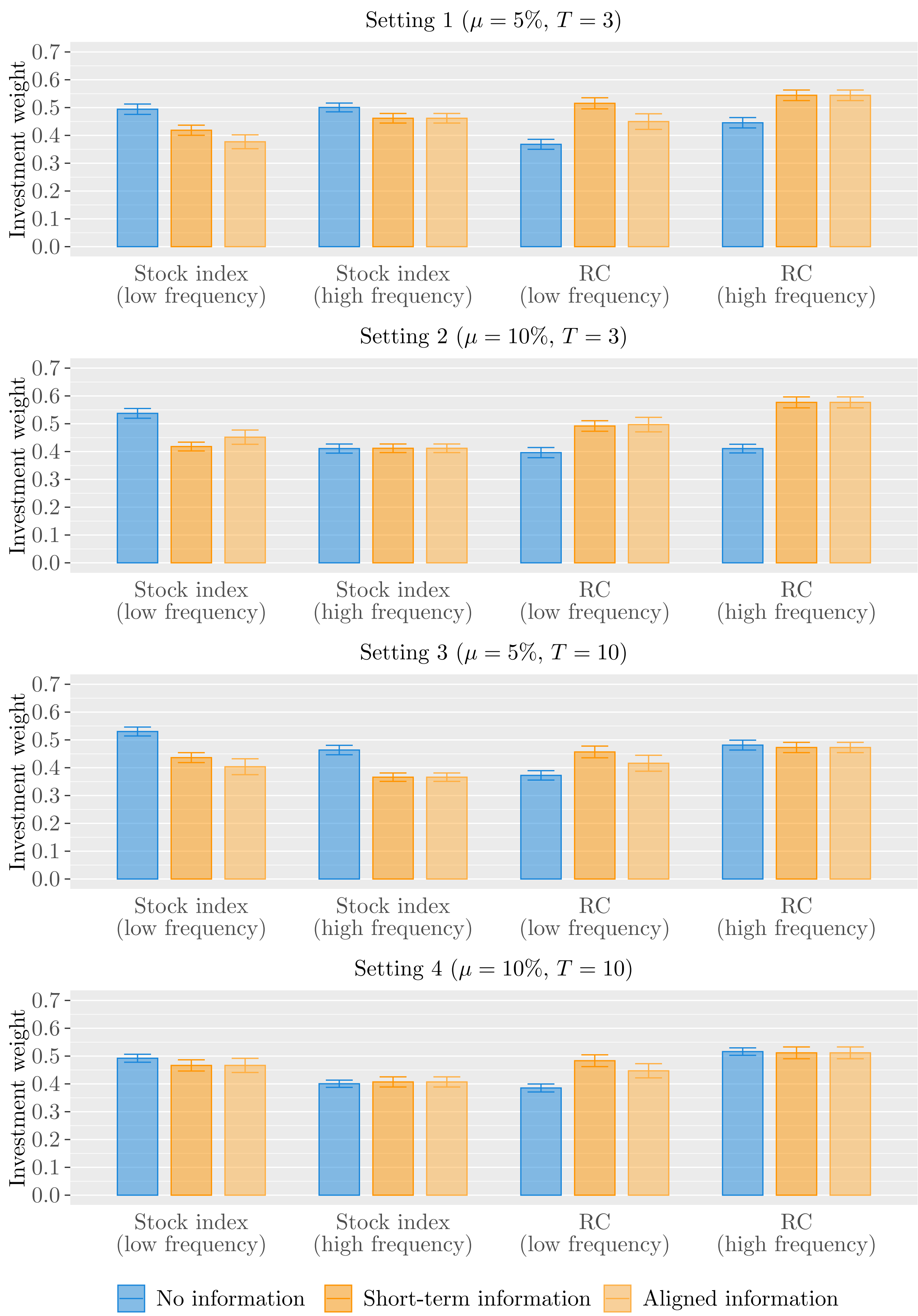


Figure 3.4.5: Average investment weights for different products (stock index and RC) and of different subject groups subdivided by experimental setting, evaluation frequency and PF. The whiskers represent standard errors.

these settings when return probability information is provided. When no probability information is provided, I expect no difference in the low-frequency groups and little to no difference in the high-frequency groups because these subjects had no possibility to reveal the risk and return characteristics of the products or a very limited possibility based on their experience from prior short-term decisions. Differences can only arise if the subjects differ between settings for instance in terms of risk preferences. Accordingly, I do not observe (uniformly) higher investment weights in settings 2 and 4 when no information is provided. When providing probability information, however, the stock index yields higher investment weights in setting 4 compared to setting 3 and also in the low-frequency group in setting 2 compared to setting 1. In the high-frequency groups in settings 1 and 2, the difference might be less obvious due to the display of short-term returns. The results for the RC are similar with larger weights in setting 4 compared to setting 3 and in setting 2 compared to setting 1 (at least for the subject group with aligned probability information).

To analyze the impact of the investment horizon, setting 1 (3 years) can be compared to setting 3 (10 years) and setting 2 (3 years) can be compared to setting 4 (10 years). Following the recommendation of most investment advisers, investment weights in stocks are expected to be greater for longer horizons. This, however, is not clearly evident from my results. The investment weights in the stock index are at a similar level in settings 2 and 4. Only when comparing the low-frequency subject groups in settings 1 and 3, one can observe larger investment weights in the stock index. For the high-frequency group rather the opposite is the case. For the RC, I even find larger weights for short-term investments (i.e., in settings 1 and 3) when return probability information is provided.

To facilitate the comparison of the low- and high-frequency subject groups, I calculate the difference between the average investment weight of the low-frequency group and the average investment weight of the high-frequency group. These differences are hereafter referred to as delta investment weights, formally defined as

$$\Delta W^{p,s,f} = \frac{1}{|L|} \sum_{i \in L} W_i^{p,s,f} - \frac{1}{|H|} \sum_{j \in H} W_j^{p,s,f}, \tag{3.19}$$

$$\text{with} \quad W_j^{p,s,f} = \frac{1}{T} \sum_{t=1}^{T} w_{j,t}^{p,s,f} \quad \text{if } j \in H, \tag{3.20}$$

and calculated for each product $p \in \{\text{stock index}, \text{RC}\}$, each setting $s \in \{1, 2, 3, 4\}$ and each PF $f \in \{\text{no information, short-term information, aligned information}\}$. $W_i^{p,s,f}$ corresponds to the investment weight of subject i. If the subject evaluated the investment frequently and thus took multiple short-term decisions, $W_i^{p,s,f}$ is defined as the average weight of all these short-term investment decisions, which are denoted by $w_{j,t}^{p,s,f}$. T is the investment horizon and corresponds to either 3 years (settings 1 and 2) or 10 years (settings 3 and 4). L and H are sets and include subjects from the low-frequency group or high-frequency group respectively. A positive (negative) delta investment weight implies that a low evaluation frequency yields higher (lower) investment weights and thus leads to an increased (decreased) willingness to take risks. A positive value is therefore in line with prior studies on MLA (see Section 3.4.2) and the general consensus that myopia reduces risk-taking. The results on the comparison between low- and high-frequency groups are plotted in Figure 3.4.6.

To test the impact of the evaluation frequency statistically, I apply two regression models. The dependent variable is $W_i^{p,s,f}$, which can be both the long-term, low-frequency weight or the average short-term, high-frequency weight. I distinguish between investment weights in different experimental settings and investment weights from different PF groups by running the regression models for each product, each setting and each PF independently. This approach allows us to investigate the impact of the evaluation frequency in the different subject groups separately in a simple manner. The regression models are specified as

$$W_i^{p,s,f} = \beta_0 + \beta_1 D_{i,LF} + \gamma Z_i + \epsilon_i^{p,s,f} \tag{I}$$

$$\text{and } W_i^{p,s,f} = \beta_0 + \beta_1 D_{i,LF} + \epsilon_i^{p,s,f}. \tag{II}$$

β_0, β_1 and γ are regression coefficients. The dummy variable $D_{i,LF}$ captures the affiliation to one of the two evaluation frequency groups. It takes on the value 1 if subject i has a low evaluation frequency. Therefore, if the regression coefficient β_1 is positive (negative), then the investment weights are larger (smaller) in the low-frequency group than in the high-frequency group. In other words, a positive (negative) β_1 implies that evaluation frequency decreases (increases) the willingness to take risks, which is (not) in line with prior studies on MLA.

Z_i is a vector of control variables and included only in the first regression model. The second regression model does not contain control variables but has the advantage that the intercept β_0 can be interpreted in a straight-forward way as the average investment weight in the high-frequency group. The average investment weight in the low-frequency group can be obtained by summing the two coefficients β_0 and β_1. The results of the regression analyses are shown in

		No information (I)	No information (II)	Short-term information (I)	Short-term information (II)	Aligned information (I)	Aligned information (II)
Setting 1	Intercept	0.50	0.50***	0.63*	0.46***	0.83**	0.46***
		(0.37)	(0.02)	(0.36)	(0.03)	(0.34)	(0.03)
	Low frequency	−0.01	−0.01	−0.02	−0.04	−0.05	−0.08**
		(0.04)	(0.03)	(0.04)	(0.04)	(0.04)	(0.04)
	Control variables	yes	no	yes	no	yes	no
	Observations	224	255	215	243	205	229
	R^2	0.27	0.0001	0.21	0.01	0.30	0.02
	Adjusted R^2	0.16	−0.004	0.08	0.002	0.18	0.02
	F Statistic	2.41***	0.03	1.58**	1.45	2.59***	5.60**
Setting 2	Intercept	0.38**	0.41***	0.31	0.41***	0.79***	0.41***
		(0.17)	(0.02)	(0.27)	(0.02)	(0.29)	(0.02)
	Low frequency	0.07**	0.13***	0.001	0.01	0.02	0.04
		(0.04)	(0.03)	(0.03)	(0.03)	(0.04)	(0.03)
	Control variables	yes	no	yes	no	yes	no
	Observations	214	230	219	239	205	225
	R^2	0.30	0.06	0.27	0.0002	0.34	0.01
	Adjusted R^2	0.20	0.05	0.17	−0.004	0.23	0.002
	F Statistic	2.89***	13.92***	2.63***	0.04	3.08***	1.38
Setting 3	Intercept	0.05	0.46***	0.06	0.37***	0.15	0.37***
		(0.19)	(0.02)	(0.25)	(0.02)	(0.21)	(0.02)
	Low frequency	0.06*	0.07**	0.04	0.07**	0.05	0.04
		(0.03)	(0.03)	(0.03)	(0.03)	(0.04)	(0.03)
	Control variables	yes	no	yes	no	yes	no
	Observations	246	267	211	226	207	227
	R^2	0.26	0.02	0.20	0.02	0.26	0.01
	Adjusted R^2	0.17	0.01	0.08	0.02	0.15	0.001
	F Statistic	2.92***	4.07**	1.66**	4.56**	2.33***	1.18
Setting 4	Intercept	−0.03	0.40***	−0.11	0.41***	0.25	0.41***
		(0.20)	(0.02)	(0.37)	(0.03)	(0.30)	(0.03)
	Low frequency	0.10***	0.09***	0.11**	0.06	0.04	0.06
		(0.03)	(0.03)	(0.04)	(0.04)	(0.04)	(0.04)
	Control variables	yes	no	yes	no	yes	no
	Observations	341	370	170	188	193	207
	R^2	0.22	0.02	0.26	0.01	0.19	0.01
	Adjusted R^2	0.15	0.02	0.12	0.01	0.06	0.01
	F Statistic	3.29***	9.29***	1.80**	2.38	1.48*	2.59

*p<0.1; **p<0.05; ***p<0.01

Table 3.4.3: Regression analysis of investment weights of the stock index in different settings

		No information (I)	No information (II)	Short-term information (I)	Short-term information (II)	Aligned information (I)	Aligned information (II)
Setting 1	Intercept	0.68*	0.45***	0.19	0.54***	0.08	0.54***
		(0.41)	(0.03)	(0.39)	(0.03)	(0.40)	(0.03)
	Low frequency	−0.12***	−0.08**	−0.04	−0.03	−0.10**	−0.09**
		(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
	Control variables	yes	no	yes	no	yes	no
	Observations	224	255	215	243	205	229
	R^2	0.17	0.02	0.16	0.002	0.19	0.02
	Adjusted R^2	0.04	0.01	0.03	−0.002	0.06	0.02
	F Statistic	1.29	4.48**	1.18	0.54	1.41*	5.66**
Setting 2	Intercept	0.25	0.41***	0.09	0.58***	−0.26	0.58***
		(0.19)	(0.02)	(0.37)	(0.03)	(0.36)	(0.03)
	Low frequency	−0.02	−0.01	−0.06	−0.08**	−0.07	−0.08**
		(0.04)	(0.03)	(0.04)	(0.04)	(0.04)	(0.04)
	Control variables	yes	no	yes	no	yes	no
	Observations	214	230	219	239	205	225
	R^2	0.11	0.001	0.15	0.02	0.22	0.02
	Adjusted R^2	−0.02	−0.004	0.03	0.02	0.09	0.01
	F Statistic	0.82	0.18	1.25	4.83**	1.72**	4.25**
Setting 3	Intercept	0.04	0.48***	0.75**	0.47***	0.31	0.47***
		(0.22)	(0.03)	(0.31)	(0.03)	(0.23)	(0.03)
	Low frequency	−0.13***	−0.11***	−0.06	−0.02	−0.07*	−0.06
		(0.04)	(0.03)	(0.04)	(0.04)	(0.04)	(0.04)
	Control variables	yes	no	yes	no	yes	no
	Observations	246	267	211	226	207	227
	R^2	0.14	0.04	0.21	0.001	0.24	0.01
	Adjusted R^2	0.04	0.03	0.10	−0.004	0.12	0.01
	F Statistic	1.35	9.82***	1.84**	0.16	2.04***	2.22
Setting 4	Intercept	0.25	0.52***	0.25	0.51***	−0.03	0.51***
		(0.22)	(0.03)	(0.42)	(0.03)	(0.33)	(0.03)
	Low frequency	−0.13***	−0.13***	0.02	−0.03	−0.06	−0.06
		(0.03)	(0.03)	(0.05)	(0.04)	(0.04)	(0.04)
	Control variables	yes	no	yes	no	yes	no
	Observations	341	370	170	188	193	207
	R^2	0.12	0.05	0.23	0.002	0.17	0.01
	Adjusted R^2	0.04	0.05	0.08	−0.003	0.04	0.01
	F Statistic	1.53**	18.62***	1.50*	0.45	1.29	2.67

*p<0.1; **p<0.05; ***p<0.01

Table 3.4.4: Regression analysis of investment weights of the RC in different settings

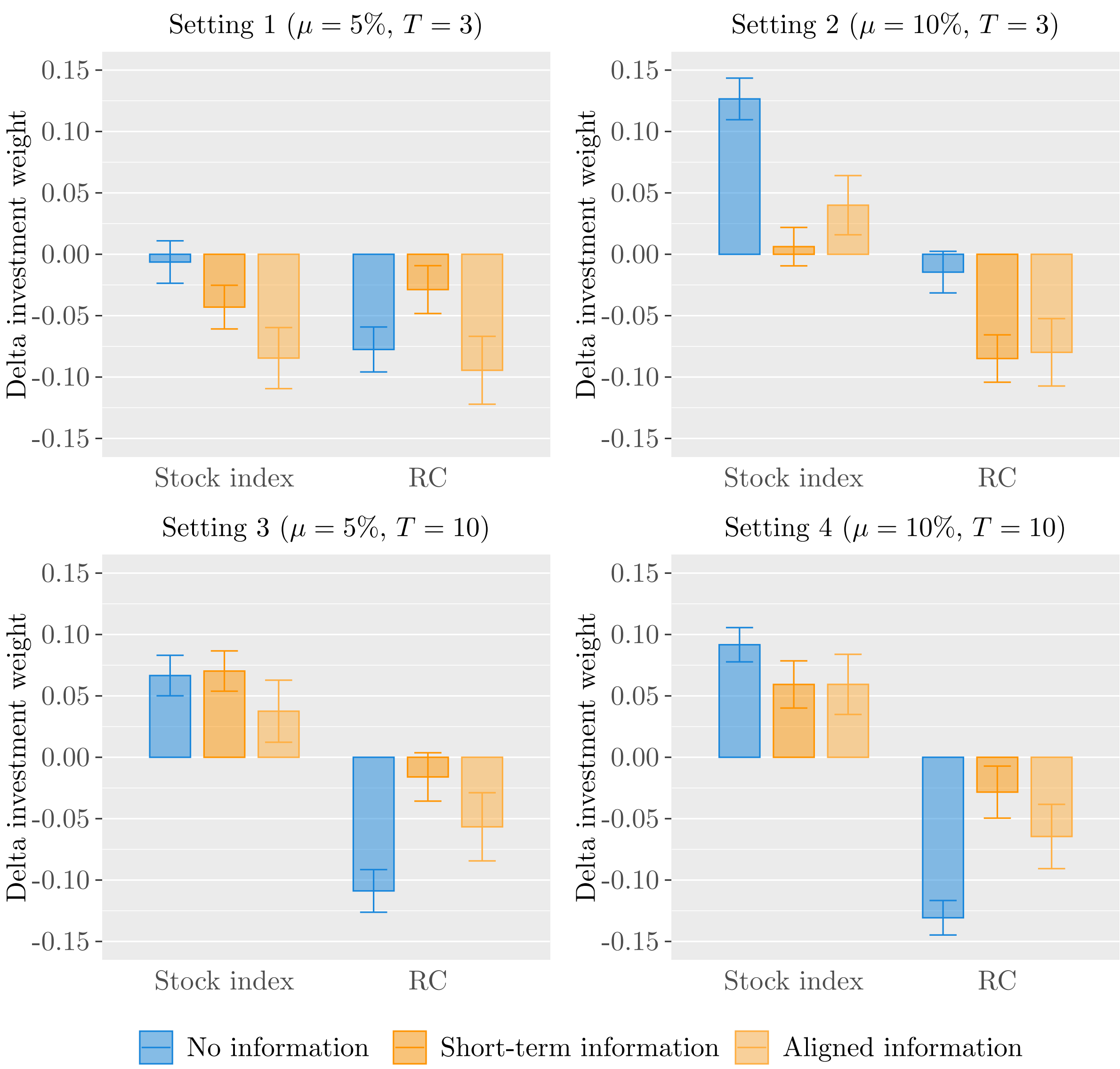


Figure 3.4.6: Delta investment weights for different products (stock index and RC) and of different subject groups subdivided by experimental setting and PF. The whiskers represent standard errors.

Table 3.4.3 for the stock index and in Table 3.4.4 for the RC.

For the stock index, delta investment weights are positive in settings 2, 3 and 4, irrespective of the PF, and mostly significant. These results are in line with prior studies showing that a low evaluation frequency increases investments in stocks. Surprisingly, the results obtained in setting 1 are not consistent with the results from other settings and suggest that a low evaluation frequency decreases stock investments. The effect of the evaluation frequency on stock investments, however, is not significant in setting 1 when controlling for differences in sample groups. Accordingly, I conclude that the experimental results are roughly in line with the theoretical analysis and prior studies suggesting that stocks are less attractive in case of frequent re-evaluations. Thus, the hypothesis H1 can be confirmed.

This picture changes drastically when considering the RC figures. There, the investment weights of the low-frequency group are lower in all settings and for all PFs, in most cases significantly, suggesting that evaluation frequency increases risk-taking. Moreover, in contrast to theoretical findings, the experimental results show that delta weights remain negative also for long-term investment horizons and large returns of the underlying asset. In fact, the difference between low- and high-frequency groups is even expanding in the long-term settings when looking at the subject group without return probability information. Thus, I can confirm hypothesis H2a, which states that myopia increases risk-taking for investments in RCs over short-term investment periods during stagnating market phases. However, I need to reject hypothesis H2b, which predicates that the inverse effect occurs for long-term investment periods or during upward trending markets phases.

A possible explanation is that the RC does not look attractive judging by the payoff diagram and product description only. The high-frequency group, however, had the opportunity to experience the product's risk and return in long-term settings, learned that the probability of receiving the maximum payoff is relatively high and subsequently increased the investment weight over time. When return probabilities were provided, investment weights were already high from the very first investment decision also for short-term investment horizons. This explanation is supported by the results plotted in Figure 3.4.5, which shows relatively high investment weights for the RC in the no information, high-frequency group in settings 3 and 4 as compared to the low-frequency group, and by my data showing a continuous increase in investment weights for the RC from the first to the last short-term decision, which is most pronounced for the no information group in settings 3 and 4.[24]

In general, however, there is no clear pattern observable for delta investment weights with regard to the PF, i.e., the return information provided does not seem to impact the degree of the effect of the evaluation frequency in a consistent manner. E.g., the magnitude of the delta weight is greatest in the aligned information group only in setting 1 but not in settings 2, 3 and 4. Thus, I can neither confirm nor reject hypothesis H3 stating that the effect of the evaluation frequency is most pronounced if aligned information is provided. Nonetheless, the extension of the experiment with multiple PFs is important to demonstrate that the effect of the evaluation

[24] The average investment weight for the RC in the no information, high-frequency group in settings 3 and 4 increased from 37.0% in the first decision to 57.5% in the last decision.

frequency is relatively robust with respect to the PF but not with respect to the risk-return profile of the risky asset.

3.4.7 Conclusion

The access to financial market data and real-time analysis tools of own investments is more common than ever today, making it easy for investors to continuously monitor and re-evaluate investments. Many scholars, however, argue that frequent evaluations lead to poor investments. The reasoning behind this argument is that continuous monitoring leads investors to experience the risk characteristics of short-term returns (e.g., daily returns as a result of daily monitoring of their portfolio value), which typically have a greater loss probability. The combined effect of people's loss aversion and high evaluation frequency, a well-known behavioral construct named as MLA, would thus induce investors to hold a relatively small share of risky assets and to miss the opportunity to realize long-term gains. The impact of MLA has been confirmed in a multitude of experimental studies (see Section 3.4.2), leading to the predominant view that a high evaluation frequency reduces risk-taking.

I challenge this view and argue that it is not universally valid but depends on the risk and return characteristics of the risky investment option. So far, the consequences of MLA have been analyzed exclusively for stocks, stock portfolios, exchange-traded funds or other linear financial products. I use cumulative prospect theory to assess the attractiveness of the distribution of asset returns over varying investment periods theoretically. The results show that the attractiveness of stock (index) returns over long-term periods is indeed relatively large, suggesting that high-frequency evaluations reduce risk-taking. However, the same analysis conducted for RCs, i.e., structured products characterized by a limited upside potential but a high probability of gaining the maximum return, yields different results: The attractiveness of RCs can actually drop when increasing the investment period to a few years if the ratio between mean return and volatility of the underlying is unfavorable.

The theoretical findings are tested with an experiment, where subjects took investment decisions in which they sequentially allocated a given investment amount to a stock index and a RC. The subject sample was split into a high-frequency group, which was evaluating their investment allocation on a yearly basis, and a low-frequency group, which took only one decision for the whole investment period. Following the reasoning of several studies on the PF in the context of MLA (Redelmeier and Tversky, 1992; Benartzi and Thaler, 1999; Beshears et al., 2017), I further differentiate between subject groups that either got no return probability information, short-term probability information, i.e., a distribution of yearly returns, or probability information aligned with the evaluation frequency, i.e., either a distribution of yearly returns (high-frequency group) or long-term returns (low-frequency group) to check the robustness of my results.

Since the theoretical analysis suggests that the effect of the evaluation frequency highly depends on the length of the investment horizon and the characteristics of the underlying asset, I conducted the experiment in four different settings with a varying mean return of the stock index and underlying (5% and 10%) and investment horizon (3 years and 10 years). Overall, a higher mean return seems to slightly increase investment weights in risky assets. A longer investment horizon, however, does not uniformly and significantly increase risk-taking. These results vary depending on the PF and type of risky asset.

With regard to my main research question on the effect of the evaluation frequency on risk-taking, my findings for stocks are in line with prior studies, suggesting that a high evaluation frequency reduces the willingness to invest in stocks. At the same time, the investment weights in the RC are mostly significantly higher in the high-frequency group. This result is relatively robust with respect to the PF and experimental setting despite the contradicting findings from the theoretical analysis.

Overall, the study disproves the common belief that myopia generally decreases risk-taking by showing that it can also have an opposite effect, which strongly depends on the risk and return characteristics of the risky investment option. The study also points out the importance for investors to make decisions based on the entire investment horizon. This is particularly critical for investments in RCs and other assets that have a relatively low loss probability but a high potential loss, because, on the one hand, they often come along with a short time to maturity such that it is natural to evaluate the investment frequently. On the other hand, decreased investment amounts in stocks induced by myopia can in the worst case only diminish long-term profits, whereas increased investment amounts in RCs due to frequent evaluations can have far-reaching consequences with large losses.

Chapter 4
CONCLUSION

The introduction of structured financial products was a major step forward for financial markets. Finally, private investors were enabled to live up their needs and expectations and to engage in trading strategies that had been reserved only for large financial institutions before. Finally, they could bet on falling markets, sideways trending markets, high volatility, low volatility, commodities and so forth with a relatively small investment budget. But the complexity of some products is so high that it is questionable whether the product features and their implications are fully understood by investors and whether their demand can be explained by rational reasons rather than exploitation by issuers. It is thus important for researchers to enhance the transparency in the market for structured products by providing meaningful insights for investors, regulators and banks whose top priority is selling products in the clients' best interest. This is also the objective of the three research projects presented in this thesis. Each of the projects counters different transparency gaps, which is described in the subsequent summaries.

The first project is about constant leverage certificates, which have not been addressed in prior studies yet. The popularity of these products is increasing rapidly, and the products' high level of comprehensibility is likely to be one of the main drivers. The constant leverage on a daily basis is, however, treacherous: Despite a positive development of the underlying asset, investments in these products can end up with large losses. As my data indicates, the vast majority of the products results in a loss after a holding period of one year. This fact is counterintuitive and often ignored in information documents. Instead, constant leverage certificates are often presented as an instrument to benefit from rising or falling prices of certain underlyings. Thus, buyers are likely to be misguided. My thesis closes this knowledge gap by providing investors with an explanation of the compounding effect to build up an intuitive understanding of the high long-term loss probability associated with this product type, with illustrations of return distributions over varying investment horizons to reveal the products' risk and return characteristics, and with a theoretical model to become familiar with the drivers of risk and return. The most important insight for any investor potentially interested in constant leverage certificates is that buying this product means betting not only on rising or falling prices but also on a low volatility, especially with extreme leverage factors and/or long investment periods. This fact should also be highlighted in information documents and by client advisers.

The second project delves into the behavioral aspects of investment decisions with structured products. So far, investors have made their decisions based on simple text descriptions and payoff profiles of the products. This proceeding does not allow for a thorough assessment of the risks involved and can lead to biased investment decisions, which are not in line with the investors' preferences. Especially inexperienced investors might be susceptible to manipulation by superficial advertisements and information documents. E.g., (barrier) reverse convertibles are often advertised to provide a "coupon" payment regardless of the price of the underlying. Since the coupon is usually significantly larger than the interest yield of bonds or deposits, the products appear as attractive investments based on such descriptions. But, unlike bonds or deposits, the repayment of the nominal value highly depends on the development of one or multiple underlying assets. To avoid such misperceptions, it is important to provide investors with return probability information.

The results of our study support this view by showing that the provision of such information can have a large impact on the perceived attractiveness of the products. The extent of the impact depends on the format of the probability information. The effect of a bar chart with ordered returns is only minor, but a return probability histogram can turn the preference order upside down in extreme cases. E.g., a capital protection product with a protection level slightly below 100% is perceived as less attractive if presented with a histogram. This perception is natural because such a product comes along with a large loss probability and people typically have a strong aversion towards losses. The results thus suggest that a presentation format with histograms best promotes investment decisions that are in accordance with investor preferences. Consequently, histograms should be considered as a necessary complement to information documents and as a crucial instrument to increase the transparency of structured products, which should be taken into account by regulators and issuers. But also investors can learn from the study. Being aware of the impact of the presentation format helps to be less susceptible to advertisements, to develop a more critical view towards complex investments, and to understand that products that seem to be too good to be true typically have drawbacks that are not apparent at first sight.

The third and last project examines the impact of the evaluation frequency on investment decisions. Many prior studies have shown that a focus on short-term returns leads to decreased risk-taking, a behavior that can be explained with myopic loss aversion. I argue, however, that the focus on short-term returns can also have an opposite effect, especially in the context of structured product investments. The reasoning behind my argument is that prior studies are focused on stocks and equity funds, whose short-term returns have a relatively large loss probability compared to long-term returns. The short-term focus consequently results in a negative perception of the investment and in reduced investment amounts. With the equivalent reasoning, a high evaluation frequency would lead to increased investment amounts if the asset under consideration has a relatively low loss probability for short-term returns. Indeed, such assets exist in the world of structured products, such as the popular reverse convertibles. The argument is backed up with a theoretical study, where the attractiveness of return distributions over a wide range of investment periods is assessed using cumulative prospect theory, a well-established framework for investment decision making. Moreover, it is supported by a large-scale experimental study, showing that frequent evaluations yield lower investment amounts in stocks and higher investment amounts in reverse convertibles, regardless of the characteristics of the underlying stocks, the presentation format and the investment horizon.

The lesson learned from this study is that it is important to evaluate returns over a period that is in line with the investment horizon. Otherwise, there is a high risk of biased investment decisions that do not correspond to investor preferences. This is particularly important for investments in structured products for two reasons. First, as my results show, the relationship between the evaluation frequency and risk-taking is inconsistent in the context of structured products, which makes it difficult to predict investor preferences based on returns over shorter or longer periods. Second, most structured products come with a limited time to maturity. Since their payoff depends on the price of the underlying at maturity, it is natural to evaluate the products' return over their lifetime. A match between the time to maturity and the investment horizon, however, is unlikely and often regarded as secondary, as structured products can either be sold on the secondary market to the issuer or a new, similar product can be bought after expiration. To ensure such a match, it is necessary that issuers provide not only many underlying assets and product types but also products with a wide range of terms. Investors should foreground the choice of a product with an appropriate time to maturity and focus on the return distribution over the whole investment horizon rather than on short-term price movements.

Structured financial products are often associated with a lack of transparency and market inefficiency, which has brought them a bad reputation in financial markets. Despite the rather critical view of this thesis, its goal is not to further stir up the bad reputation and aversion against these products. On the contrary, and despite the already considerable market size, I believe that structured products still have a lot of potential. But to exploit this potential, it is important that these products are no longer considered as a riddle wrapped up in an enigma. I hope that the insights provided in this thesis will make a contribution in this regard and that the recommendations derived therefrom will help to improve investment decisions in the context of structured products.

BIBLIOGRAPHY

Allais, M. (1953). Le comportement de l'homme rationnel devant le risque: Critique des postulats et axiomes de l'ecole americaine. *Econometrica*, 21(4):503–546.

Andersen, T. G. and Bollerslev, T. (1998). Answering the skeptics: Yes, standard volatility models do provide accurate forecasts. *International Economic Review*, 39(453):885–905.

Anic, V. and Wallmeier, M. (2020). Perceived attractiveness of structured financial products: The role of presentation format and reference instruments. *Journal of Behavioral Finance*, 21(1):78–102.

Avellaneda, M. and Zhang, S. (2010). Path-dependence of leveraged ETF returns. *SIAM Journal on Financial Mathematics*, 1(1):586–603.

Bansal, V. K. and Marshall, J. F. (2015). A tracking error approach to leveraged ETFs: Are they really that bad? *Global Finance Journal*, 26:47–63.

Bellemare, C., Krause, M., Kröger, S., and Zhang, C. (2005). Myopic loss aversion: Information feedback vs. investment flexibility. *Economics Letters*, 87(3):319–324.

Benartzi, S. and Thaler, R. H. (1995). Myopic loss aversion and the equity premium puzzle. *The Quarterly Journal of Economics*, 110(1):73–92.

Benartzi, S. and Thaler, R. H. (1999). Risk aversion or myopia? Choices in repeated gambles and retirement investments. *Management Science*, 45(3):364–381.

Beshears, J., Choi, J. J., Laibson, D., and Madrian, B. C. (2017). Does aggregated returns disclosure increase portfolio risk taking? *The Review of Financial Studies*, 30(6):1971–2005.

Blais, A.-R. and Weber, E. U. (2006). A domain-specific risk-taking (DOSPERT) scale for adult populations. *Judgment and Decision Making*, 1(1):33–47.

Blümke, A. (2009). *How to Invest in Structured Products: A Guide for Investors and Asset Managers*. John Wiley and Sons.

Bondt, W. F. and Thaler, R. (1985). Does the stock market overreact? *The Journal of Finance*, 40(3):793–805.

Bordalo, P., Gennaioli, N., and Shleifer, A. (2012). Salience theory of choice under risk. *The Quarterly Journal of Economics*, 127(3):1243–1285.

Bradbury, M. A., Hens, T., and Zeisberger, S. (2015). Improving investment decisions with simulated experience. *Review of Finance*, 19(3):1019–1052.

Bratvold, D. (2017). What is crowdsourcing? Retrieved from `https://dailycrowdsource.com/training/crowdsourcing/what-is-crowdsourcing`.

Burson, K. A., Larrick, R. P., and Lynch Jr, J. G. (2009). Six of one, half dozen of the other: Expanding and contracting numerical dimensions produces preference reversals. *Psychological Science*, 20(9):1074–1078.

Cao, J. and Rieger, M. O. (2013). Risk classes for structured products: Mathematical aspects and their implications on behavioral investors. *Annals of Finance*, 9(2):167–183.

Charupat, N. and Miu, P. (2011). The pricing and performance of leveraged exchange-traded funds. *Journal of Banking and Finance*, 35(4):966–977.

Cheng, M. and Madhavan, A. (2009). The dynamics of leveraged and inverse exchange-traded funds. *Journal of Investment Management*, 7(4):43–62.

Cohen, J. (1988). *Statistical Power Analysis for the Behavioral Sciences*, volume 2. Lawrence Erlbaum Associates.

DDV (2017). Value at risk (VaR). Retrieved from `https://www.derivateverband.de/ENG/Transparency/ValueAtRisk`.

Dean, A., Voss, D., and Draguljic, D. (2017). *Design and Analysis of Experiments*, volume 2. Springer.

Dierkes, M., Erner, C., and Zeisberger, S. (2010). Investment horizon and the attractiveness of investment strategies: A behavioral approach. *Journal of Banking and Finance*, 34(5):1032–1046.

Döbeli, B. and Vanini, P. (2010). Stated and revealed investment decisions concerning retail structured products. *Journal of Banking and Finance*, 34(6):1400–1411.

Engle, R. (2001). GARCH 101: The use of ARCH/GARCH models in applied econometrics. *Journal of Economic Perspectives*, 15(4):157–168.

Entrop, O., Peters, C., and Wilkens, M. (2012). Valuation and properties of leverage endless knock-out certificates on government bond futures. Working paper available at `https://www.retailinvestmentconference.org/files/eric_submission_full_056.pdf`.

Entrop, O., Scholz, H., and Wilkens, M. (2009). The price-setting behavior of banks: An analysis of open-end leverage certificates on the German market. *Journal of Banking and Finance*, 33(5):874–882.

Eriksen, K. W. and Kvaløy, O. (2009). Myopic investment management. *Review of Finance*, 14(3):521–542.

Etf.com (2019). Leveraged ETF overview. Retrieved from `https://www.etf.com/channels/leveraged-etfs`.

Eusipa (2019a). Eusipa derivative map. Retrieved from `https://eusipa.org/wp-content/uploads/European_map_20200213_web.pdf`.

Eusipa (2019b). Eusipa market report on structured investment products. Retrieved from `https://eusipa.org/wp-content/uploads/EUSIPA-Q3-2019-market-report_final.pdf`.

Fama, E. F. (1970). Efficient capital markets: A review of theory and empirical work. *The Journal of Finance*, 25(2):383–417.

Faraj, K. and Khaled, A. (2019). Sure time to grasp the potential of structured products. Retreived from `https://www.bloomberg.com/professional/blog/sure-time-to-grasp-the-potential-of-structured-products/`.

Faul, F., Erdfelder, E., Lang, A.-G., and Buchner, A. (2007). G* Power 3: A flexible statistical power analysis program for the social, behavioral, and biomedical sciences. *Behavior Research Methods*, 39(2):175–191.

Fellner, G. and Sutter, M. (2009). Causes, consequences, and cures of myopic loss aversion: An experimental investigation. *The Economic Journal*, 119(537):900–916.

French, K. R. and Poterba, J. M. (1991). Investor diversification and international equity markets. *The American Economic Review*, 81(2):222–226.

Giese, G. (2010). On the risk-return profile of leveraged and inverse ETFs. *Journal of Asset Management*, 11(4):219–228.

Gilovich, T. (2008). *How We Know What Isn't So: The Fallibility of Human Reason in Everyday Life*. Simon and Schuster.

Gneezy, U., Kapteyn, A., and Potters, J. (2003). Evaluation periods and asset prices in a market experiment. *The Journal of Finance*, 58(2):821–837.

Gneezy, U. and Potters, J. (1997). An experiment on risk taking and evaluation periods. *The Quarterly Journal of Economics*, 112(2):631–645.

Goldstein, D. G., Johnson, E. J., and Sharpe, W. F. (2008). Choosing outcomes versus choosing products: Consumer-focused retirement investment advice. *Journal of Consumer Research*, 35(3):440–456.

Haigh, M. S. and List, J. A. (2005). Do professional traders exhibit myopic loss aversion? An experimental analysis. *The Journal of Finance*, 60(1):523–534.

Hansen, P. R. and Lunde, A. (2005). A forecast comparison of volatility models: Does anything beat a GARCH (1,1)? *Journal of Applied Econometrics*, 20(7):873–889.

Hens, T. and Rieger, M. O. (2014). Can utility optimization explain the demand for structured investment products? *Quantitative Finance*, 14(4):673–681.

Hertwig, R., Barron, G., Weber, E. U., and Erev, I. (2004). Decisions from experience and the effect of rare events in risky choice. *Psychological Science*, 15(8):534–539.

Hirshleifer, D. and Hong Teoh, S. (2003). Herd behaviour and cascading in capital markets: A review and synthesis. *European Financial Management*, 9(1):25–66.

Hogarth, R. M. and Soyer, E. (2015). Communicating forecasts: The simplicity of simulated experience. *Journal of Business Research*, 68(8):1800–1809.

Hsee, C. K. (1998). Less is better: When low-value options are valued more highly than high-value options. *Journal of Behavioral Decision Making*, 11(2):107–121.

Huber, O. (2009). *Das psychologische Experiment: Eine Einführung*. Verlag Hans Huber.

Ibrekk, H. and Morgan, M. G. (1987). Graphical communication of uncertain quantities to nontechnical people. *Risk Analysis*, 7(4):519–529.

Jarrow, R. A. (2010). Understanding the risk of leveraged ETFs. *Finance Research Letters*, 7(3):135–139.

Kachelmeier, S. J. and Shehata, M. (1992). Examining risk preferences under high monetary incentives: Experimental evidence from the People's Republic of China. *The American Economic Review*, 82(5):1120–1141.

Kahneman, D., Knetsch, J. L., and Thaler, R. H. (1991). Anomalies: The endowment effect, loss aversion, and status quo bias. *The Journal of Economic Perspectives*, 5(1):193–206.

Kahneman, D. and Tversky, A. (1972). Subjective probability: A judgment of representativeness. *Cognitive Psychology*, 3(3):430–454.

Kahneman, D. and Tversky, A. (1979). Prospect theory: An analysis of decision under risk. *Econometrica*, 47(2):263–291.

Kaufmann, C., Weber, M., and Haisley, E. (2013). The role of experience sampling and graphical displays on one's investment risk appetite. *Management Science*, 59(2):323–340.

Koopman, S. J., Jungbacker, B., and Hol, E. (2005). Forecasting daily variability of the S&P 100 stock index using historical, realised and implied volatility measurements. *Journal of Empirical Finance*, 12(3):445–475.

Kunz, A. H., Messner, C., and Wallmeier, M. (2017). Investors risk perceptions of structured financial products with worst-of payout characteristics. *Journal of Behavioral and Experimental Finance*, 15(15):66–73.

Langer, T. and Weber, M. (2001). Prospect theory, mental accounting, and differences in aggregated and segregated evaluation of lottery portfolios. *Management Science*, 47(5):716–733.

Langer, T. and Weber, M. (2005). Myopic prospect theory vs. myopic loss aversion: How general is the phenomenon? *Journal of Economic Behavior and Organization*, 56(1):25–38.

Langer, T. and Weber, M. (2008). Does commitment or feedback influence myopic loss aversion? An experimental analysis. *Journal of Economic Behavior and Organization*, 67(3–4):810–819.

Leland, H. E. (1999). Beyond mean-variance: Performance measurement in a nonsymmetrical world. *Financial Analysts Journal*, 55(1):27–36.

Lindauer, T. and Seiz, R. (2008). Pricing (multi-) barrier reverse convertibles. SSRN working paper no. 1160297.

Loviscek, A., Tang, H., and Xu, X. E. (2014). Do leveraged exchange-traded products deliver their stated multiples? *Journal of Banking and Finance*, 43(1):29–47.

Lu, L., Wang, J., and Zhang, G. (2009). Long term performance of leveraged ETFs. SSRN working paper no. 1344133.

Mehra, R. and Prescott, E. C. (1985). The equity premium: A puzzle. *Psychological Review*, 15(2):145–161.

Murphy, R. and Wright, C. (2010). An empirical investigation of the performance of commodity-based leveraged ETFs. *Journal of Index Investing*, 1(3):14–23.

Nickerson, R. S. (1998). Confirmation bias: A ubiquitous phenomenon in many guises. *Review of General Psychology*, 2(2):175–220.

Odean, T. (1998). Volume, volatility, price, and profit when all traders are above average. *The Journal of Finance*, 53(6):1887–1934.

Ofir, M. and Wiener, Z. (2012). Investor sophistication and the effect of behavioral biases in structured products investment. SSRN working paper no. 2193287.

Palan, S. and Schitter, C. (2018). Prolific.ac: A subject pool for online experiments. *Journal of Behavioral and Experimental Finance*, 17:22–27.

Park, C. W. and Lessig, V. P. (1981). Familiarity and its impact on consumer decision biases and heuristics. *Journal of Consumer Research*, 8(2):223–230.

Read, D. (2005). Monetary incentives, what are they good for? *Journal of Economic Methodology*, 12(2):265–276.

Redelmeier, D. A. and Tversky, A. (1992). On the framing of multiple prospects. *Psychological Science*, 3(3):191–193.

Rieger, M. O. (2012). Why do investors buy bad financial products? Probability misestimation and preferences in financial investment decision. *Journal of Behavioral Finance*, 13(2):108–118.

Rieger, M. O. (2016). *Optionen, Derivate und strukturierte Produkte*. Schäffer-Poeschel.

Rieger, M. O. and Hens, T. (2012). Explaining the demand for structured financial products: Survey and field experiment evidence. *Zeitschrift für Betriebswirtschaft*, 82(5):491–508.

Rieger, M. O., Wang, M., and Hens, T. (2014). Risk preferences around the world. *Management Science*, 61(3):637–648.

Rosenthal, R. and Fode, K. L. (1963). The effect of experimenter bias on the performance of the albino rat. *Systems Research and Behavioral Science*, 8(3):183–189.

Rossetto, S. and Van Bommel, J. (2009). Endless leverage certificates. *Journal of Banking and Finance*, 33(8):1543–1553.

Sabbatini, M. and Linton, O. (1998). A GARCH model of the implied volatility of the Swiss market index from option prices. *International Journal of Forecasting*, 14(2):199–213.

Samuelson, P. A. (1963). Risk and uncertainty: A fallacy of large numbers. *Scientia*, 98:108–113.

Samuelson, W. and Zeckhauser, R. (1988). Status quo bias in decision making. *Journal of Risk and Uncertainty*, 1(1):7–59.

Sharpe, W. F. (2011). *Investors and Markets: Portfolio Choices, Asset Prices, and Investment Advice*. Princeton University Press.

Sharpe, W. F., Goldstein, D. G., and Blythe, P. W. (2000). The distribution builder: A tool for inferring investor preferences. Working paper available at `http://www.stanford.edu/œwfsharpe/art/qpaper/qpaper.html`.

Shefrin, H. and Statman, M. (1985). The disposition to sell winners too early and ride losers too long: Theory and evidence. *The Journal of Finance*, 40(3):777–790.

Smith, V. L. and Walker, J. M. (1993). Monetary rewards and decision cost in experimental economics. *Economic Inquiry*, 31(2):245–261.

Stier, W. (1996). *Empirische Forschungsmethoden.* Springer.

Stoimenov, P. A. and Wilkens, S. (2005). Are structured products 'fairly' priced? An analysis of the German market for equity-linked instruments. *Journal of Banking and Finance*, 29(12):2971–2993.

SVSP (2015). SVSP Risikoklassifizierung (Value at Risk) – FAQ. Retrieved from http://www.svsp-verband.ch/wp-content/uploads/2015/08/SVSP_Risikokennzahl_FAQ_de_2013-02-01.pdf.

Tang, H. and Xu, X. E. (2013). Solving the return deviation conundrum of leveraged exchange-traded funds. *Journal of Financial and Quantitative Analysis*, 48(1):309–342.

Thaler, R. H., Tversky, A., Kahneman, D., and Schwartz, A. (1997). The effect of myopia and loss aversion on risk taking: An experimental test. *The Quarterly Journal of Economics*, 112(2):647–661.

Trainor, Jr., W. (2011). Daily vs. monthly rebalanced leveraged funds. *Journal of Finance and Accountancy*, 6:1–14.

Tversky, A. and Kahneman, D. (1973). Availability: A heuristic for judging frequency and probability. *Cognitive Psychology*, 5(2):207–232.

Tversky, A. and Kahneman, D. (1974). Judgment under uncertainty: Heuristics and biases. *Science*, 185(4157):1124–1131.

Tversky, A. and Kahneman, D. (1981). The framing of decisions and the psychology of choice. *Science*, 211(4481):453–458.

Tversky, A. and Kahneman, D. (1983). Extensional versus intuitive reasoning: The conjunction fallacy in probability judgment. *Psychological Review*, 90(4):293–315.

Tversky, A. and Kahneman, D. (1986). Rational choice and the framing of decisions. *Journal of Business*, 59(4):251–278.

Tversky, A. and Kahneman, D. (1992). Advances in prospect theory: Cumulative representation of uncertainty. *Journal of Risk and uncertainty*, 5(4):297–323.

Vrecko, D., Klos, A., and Langer, T. (2009). Impact of presentation format and self-reported risk aversion on revealed skewness preferences. *Decision Analysis*, 6(2):57–74.

Wallmeier, M. (2011). Beyond payoff diagrams: How to present risk and return characteristics of structured products. *Financial Markets and Portfolio Management*, 25(3):313–338.

Wallmeier, M. and Diethelm, M. (2009). Market pricing of exotic structured products: The case of multi-asset barrier reverse convertibles in Switzerland. *The Journal of Derivatives*, 17(2):59–72.

Wallmeier, M. and Diethelm, M. (2012). Multivariate downside risk: Normal versus variance gamma. *Journal of Futures Markets*, 32(5):431–458.

Weber, E. U., Siebenmorgen, N., and Weber, M. (2005). Communicating asset risk: How name recognition and the format of historic volatility information affect risk perception and investment decisions. *Risk Analysis*, 25(3):597–609.

Weber, M. and Camerer, C. F. (1998). The disposition effect in securities trading: An experimental analysis. *Journal of Economic Behavior and Organization*, 33(2):167–184.

Wilkens, S. and Stoimenov, P. A. (2007). The pricing of leverage products: An empirical investigation of the German market for 'long' and 'short' stock index certificates. *Journal of Banking and Finance*, 31(3):735–750.

Zeisberger, S. (2016). Do people care about loss probabilities? SSRN working paper no. 2169394.

Appendices

Appendix A

CONSTANT LEVERAGE CERTIFICATES

A.1 Descriptive Statistics of Nominal and Ordinal Variables

Variable	Levels	n	%
Issuer	Commerzbank	112	33.0
	Vontobel	227	67.0
Factor	-15	4	1.2
	-12	5	1.5
	-10	12	3.5
	-8	8	2.4
	-6	28	8.3
	-5	43	12.7
	-4	16	4.7
	-3	5	1.5
	3	13	3.8
	4	53	15.6
	5	80	23.6
	6	33	9.7
	8	10	3.0
	10	14	4.1
	12	10	3.0

Variable	Levels	n	%
	15	5	1.5
Product currency	CHF	304	89.7
	EUR	33	9.7
	USD	2	0.6
Typ of underlying	equity	244	72.0
	index	95	28.0
Underlying	DAX	17	5.0
	DJIA	11	3.2
	Euro Stoxx 50	11	3.2
	MDAX	8	2.4
	Nasdaq 100	16	4.7
	Nikkei 225	8	2.4
	Others	230	67.8
	S&P 500	12	3.5
	Swatch	9	2.6
	UBS	9	2.6
	Volkswagen	8	2.4
Currency of the underlying	CHF	110	32.5
	EUR	145	42.8
	GBP	10	3.0
	JPY	8	2.4
	NOK	1	0.3
	USD	65	19.2

A.2 Descriptive Statistics of Issuer Fees

Variable	Min	q_1	q_2	q_3	Max	Mean	Sd
Index fee	0.007	0.007	0.010	0.010	0.015	0.009	0.002
Financing spread	0.001	0.001	0.001	0.005	0.025	0.004	0.005
Short rate	0.001	0.001	0.001	0.008	0.250	0.007	0.023

Appendix B

PERCEIVED ATTRACTIVENESS OF STRUCTURED PRODUCTS

B.1 Overview of Variables and Measures

Dependent Variables

Attractiveness adjusted product. Ordinal variable that indicates the perceived attractiveness of the volatility-adjusted product in the third investment decision.

Attractiveness CPP. Ordinal variable that indicates the perceived attractiveness of the CPP in the first investment decision.

Attractiveness individual product. Ordinal variable that indicates the perceived attractiveness of the self-designed structured product in the third investment decision.

Attractiveness stock. Ordinal variable that indicates the perceived attractiveness of the stock in the first investment decision.

Attractiveness RC. Ordinal variable that indicates the perceived attractiveness of the RC in the first investment decision.

Investment weight adjusted product. Investment weight of the volatility-adjusted product in the third investment decision.[1]

Investment weight CPP. Investment weight of the CPP in the first investment decision.[2]

---

[1] The sum of the two investment weights (adjusted and individual product) in the second investment decision is equal to 1.

[2] The sum of the three investment weights (stock, CPP and RC) in the first investment decision is equal to 1.

Investment weight individual product. Investment weight of the self-designed structured product in the third investment decision.[1]

Investment weight stock. Investment weight of the stock in the first investment decision.[2]

Investment weight RC. Investment weight of the RC in the first investment decision.[2]

Maximum payoff. Chosen upper payoff limit of the self-designed structured product in the second investment decision ranging from 10 000 (investment budget) to 20 000.

Minimum payoff. Chosen capital protection level of the self-designed structured product in the second investment decision ranging from 0 to 10 000 (investment budget).

Slope. Chosen slope in the middle section of the payoff diagram between the minimum and maximum payoff of the self-designed structured product in the second investment decision ranging from 0.2 to 3.2.

Treatment Variables

PF. Categorical variable that indicates the PF to which the subject is assigned (PF 1, PF 2 or PF 3).

Risk Preference Measures

Risk preference measure 1. Certainty equivalent to a lottery with a 60% chance to win 100.

Risk preference measure 2. 100 deducted by the (absolute value of the) certainty equivalent for a lottery with a 60% chance to lose 100.

Risk preference measure 3. Ordinal variable that indicates the likelihood of investing 10% of the annual income in a moderate growth diversified fund.

Risk preference measure 4. Ordinal variable that indicates the likelihood of investing 5% of the annual income in a very speculative stock.

Risk preference measure 5. Ordinal variable that indicates the likelihood of investing 10% of the annual income in a new business venture.

Experience Measures

Experience measure 1. Ordinal variable that indicates familiarity with statistics.

Experience measure 2. Ordinal variable that indicates familiarity with structured financial products.

Experience measure 3. Dummy variable that takes the value 1 if the subject has already invested in structured financial products and 0 if not.

Experience measure 4. Dummy variable that takes the value 1 if the subject has already invested in stocks, funds, bonds or derivatives and 0 if not.

Demographic Variables

Age. Age in years.

Education. Ordinal variable that indicates the highest degree.

Gender. Categorical variable that indicates whether the subject is male or female.

Income. Ordinal variable that indicates the monthly net income.

Profession. Categorical variable that indicates whether the subject is unemployed, in school, employed, self-employed or retired (main activity).

Other Control Variables

Experiment 2. Dummy variable that takes the value 1 if the subject participated in Experiment 2 and 0 if the subject participated in Experiment 1.

Language. Categorical variable that indicates whether the experiment was completed in German or in English.

Order 1. Categorical variable that indicates whether the CPP is displayed on the left and the RC on the right in the first investment decision or the opposite way around.

Order 2. Categorical variable that indicates whether the adjusted product is displayed on the left and the individual product on the right in the third investment decision or the opposite way around.

Payoff. Dummy variable that takes the value 1 if the subject received a real monetary payoff and 0 if the subject has not picked up the payoff.

Survey type. Categorical variable that indicates whether the experiment was completed online and or in a controlled setting.

B.2 Experiment

Instructions

Dear participant

The following is a survey on structured financial products. Structured financial products are popular innovative investment instruments. They are mostly issued by banks and offered to (private) customers for investment.

The survey takes about 20 minutes. Participation in the survey is voluntary.

The survey is anonymous, which means that the answers cannot be assigned to the participants at any time. The data will be treated confidentially and used only for research purposes.

Please make sure your screen is not too narrow. A mobile phone is not suitable for the survey.

For participation in the survey, you will receive a compensation with an expected value of CHF 15. **The amount paid is proportional to a simulated return on the assets you have selected.** You will get more information about the payoff at the end of the survey.

Many thanks in advance for your participation!

Attention: There is no "back" button.

NEXT

Page 1: Financial Knowledge and Experience

Are you familiar with statistics?

- Yes, I am very familiar with statistics.
- I know the basics.
- No, I have never dealt with it.

Are you familiar with structured financial products?

- Yes, I am very familiar with structured financial products.
- I could roughly explain structured financial products.
- I know roughly what they are.
- I have already heard of them.
- No, I have never heard of them.

Have you already invested in structured financial products?

- Yes
- No

Have you already invested in shares, funds, bonds or derivatives/options?

- Yes
- No

NEXT

Page 1 of 7

Page 2: Risk Preferences

For each of the following statements, please indicate the likelihood that you would engage in the described activity or behavior if you were to find yourself in that situation.

Investing 10% of your annual income in a moderate growth diversified fund.

- Extremely unlikely
- Moderately unlikely
- Somewhat unlikely
- Not sure
- Somewhat likely
- Moderately likely
- Extremely likely

Investing 5% of your annual income in a very speculative stock.

- Extremely unlikely
- Moderately unlikely
- Somewhat unlikely
- Not sure
- Somewhat likely
- Moderately likely
- Extremely likely

Investing 10% of your annual income in a new business venture.

- Extremely unlikely
- Moderately unlikely
- Somewhat unlikely
- Not sure
- Somewhat likely
- Moderately likely
- Extremely likely

Imagine you are offered the lottery below.

With a probability of 60% you get CHF 100
and with a probability of 40% you get CHF 0.
Please indicate the maximum amount you are willing to pay to participate in the lottery.

The following lottery includes losses. Imagine you have to participate in the lottery, unless you pay a certain amount before the lottery.

With a probability of 60% you lose CHF 100
and with a probability of 40% you lose CHF 0.
Please indicate the maximum amount you are willing to pay to avoid the lottery.

NEXT

Page 2 of 7

Page 3: Introduction of the Stock, CPP and RC

In the following, you will have the possibility to invest in three investment options: a stock and two different structured products.
Imagine that the investment period is one year and the investment capital amounts to CHF 10'000.

First, the three assets are explained. A diagram shows the profit or loss of the products as a function of the stock price at the end of the investment period. More information about the charts appears when you move the cursor over the respective chart.

If you understand the assets, click on "next".

STOCK

Stocks are assets that represent shares in a company. The value of stocks can rise (unlimited) or fall (in extreme cases down to zero).

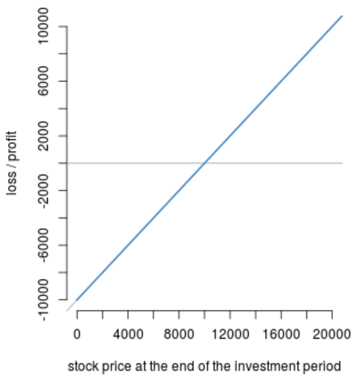
STRUCTURED PRODUCT A

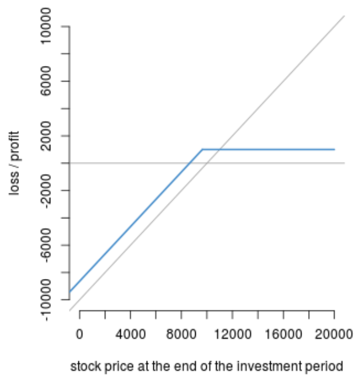
STRUCTURED PRODUCT B

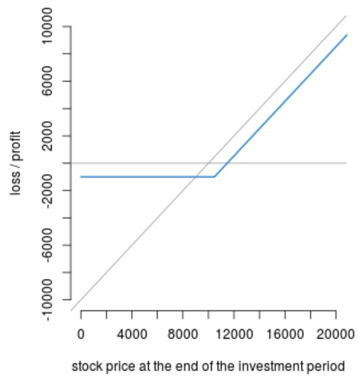
The values of the structured products A and B depend on the development of the stock price (same stock as on the left).

Structured product A has a limited upside potential. The value at the end of the investment period is at most 110% of the original value. The product therefore has a limited profit in the case of a favorable development of the stock price, but the loss in the case of an unfavorable stock price development is lower than the loss of holding the stock.

Structured product B has a limited loss in value. The value at the end of the investment period is at least 90% of the original value. The product is therefore protected against large losses in the case of an unfavorable development of the stock price, but the profit is lower compared to holding the stock in the case of a favorable development of the stock price.







NEXT

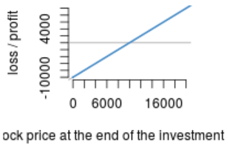
Page 3 of 7

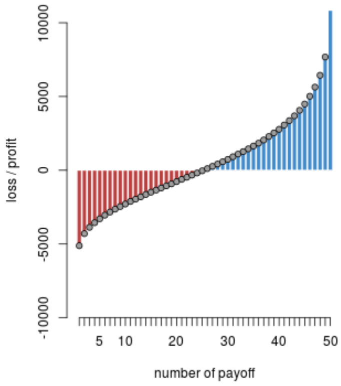
Page 4: First Investment Decision

An analysis of the assets generated new findings regarding the probability of the level of profit or loss.

The additional chart below shows a representative selection of 50 payoffs, all of which occur with the same probability of 2%. The profit or loss level is shown on the vertical axis. The red and blue bars of this chart represent the respective product, and the gray dots represent the stock.

STOCK

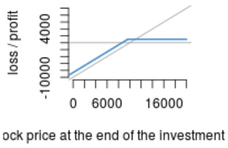


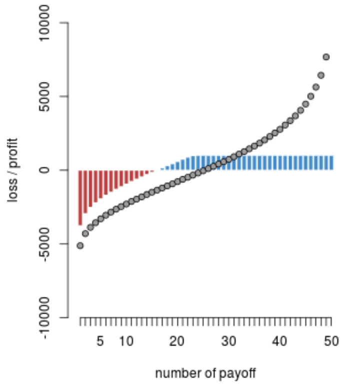


How attractive is the stock to you in comparison to the other assets?

- Very attractive
- Rather attractive
- Mediocre
- Rather unattractive
- Very unattractive

STRUCTURED PRODUCT A

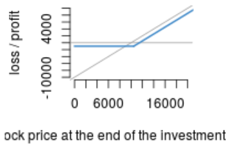


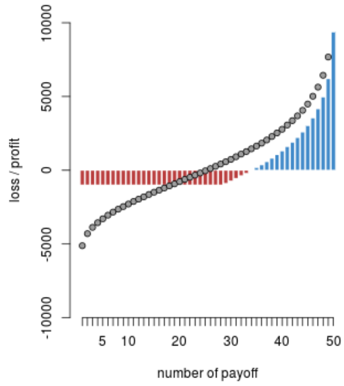


How attractive is structured product A to you in comparison to the other assets?

- Very attractive
- Rather attractive
- Mediocre
- Rather unattractive
- Very unattractive

STRUCTURED PRODUCT B





How attractive is structured product B to you in comparison to the other assets?

- Very attractive
- Rather attractive
- Mediocre
- Rather unattractive
- Very unattractive

Imagine that you invest CHF 10'000 in the assets for one year. What percentage of your capital would you invest in which asset?
Use the sliders to specify the result. The total percentage must be 100%.

Percentage in stocks

0% 100%
0 10 20 30 40 50 60 70 80 90 100

Percentage in structured product A

0% 100%
0 10 20 30 40 50 60 70 80 90 100

Percentage in structured product B

0% 100%
0 10 20 30 40 50 60 70 80 90 100

Total investment: 0%

NEXT

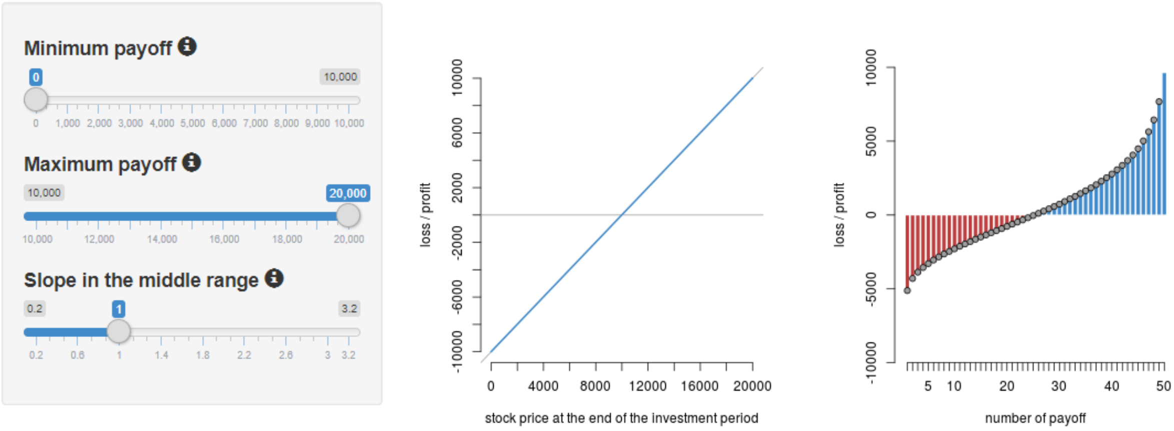
Page 4 of 7

Page 5: Second Investment Decision/Tailor-made Structured Product Design

In the following, you have the possibility to design your own structured financial product.

To do so, use the sliders to determine the minimum payoff, the maximum payoff and the slope between them. For more information about this, move the cursor over the respective setting.

Again, imagine that you invest CHF 10'000 for one year in the designed product.



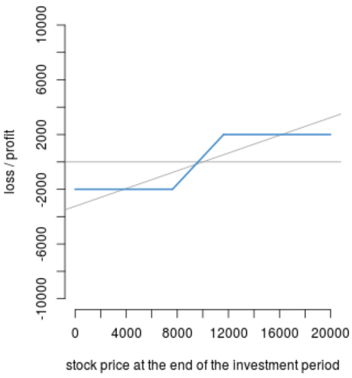
NEXT

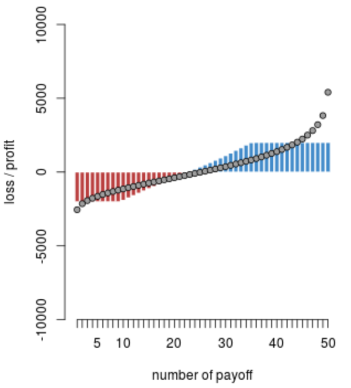
Page 5 of 7

Page 6: Third Investment Decision

In the following, you once more have the possibility to invest in two different products: product C and product D.
More information about the charts appears when you move the cursor over the respective chart.

PRODUCT C

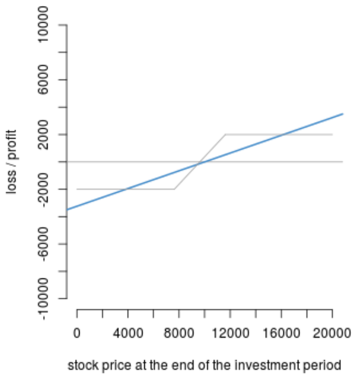


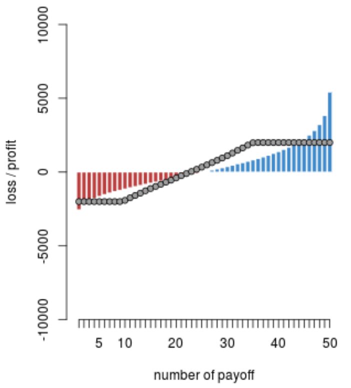


How attractive is product C to you?

- Very attractive
- Rather attractive
- Mediocre
- Rather unattractive
- Very unattractive

PRODUCT D



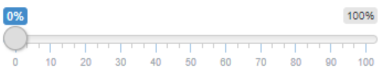


How attractive is product D to you?

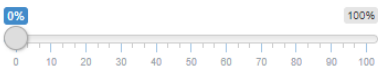
- Very attractive
- Rather attractive
- Mediocre
- Rather unattractive
- Very unattractive

Again, imagine that you invest CHF 10'000 in the products for one year. What percentage of your capital would you invest in which product?
Use the sliders to specify the result. The total percentage must be 100%.

Percentage in product C



Percentage in product D



Total investment: 0%

NEXT

Page 6 of 7

Page 7: Demographics

Finally, we would like to ask you a few questions about yourself.

Please indicate your gender.

- Male
- Female

How old are you?

Please indicate your marital status.

- Unmarried
- Married
- Divorced
- Widowed

Please indicate your nationality.

Please indicate your highest degree.

- No degree
- Elementary school graduation
- Completed apprenticeship
- High school degree
- Bachelor's degree or equivalent
- Master's degree or equivalent
- Doctor's degree or equivalent

Please indicate your profession (main activity).

- Unemployed
- Student or in school
- Employed
- Self-employed
- Retired

Please indicate your average monthly net income.

- < CHF 1'000
- CHF 1'000 - 3'000
- CHF 3'000 - 5'000
- CHF 5'000 - 10'000
- > CHF 10'000

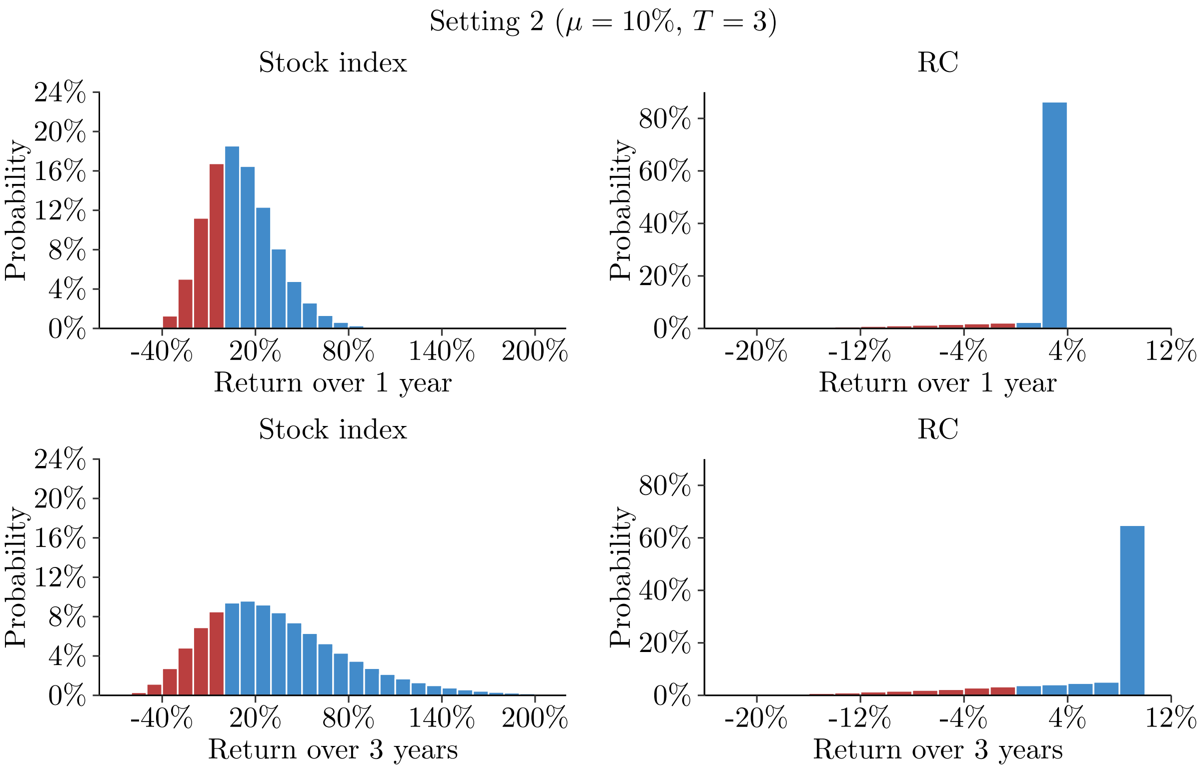
SUBMIT

Page 7 of 7

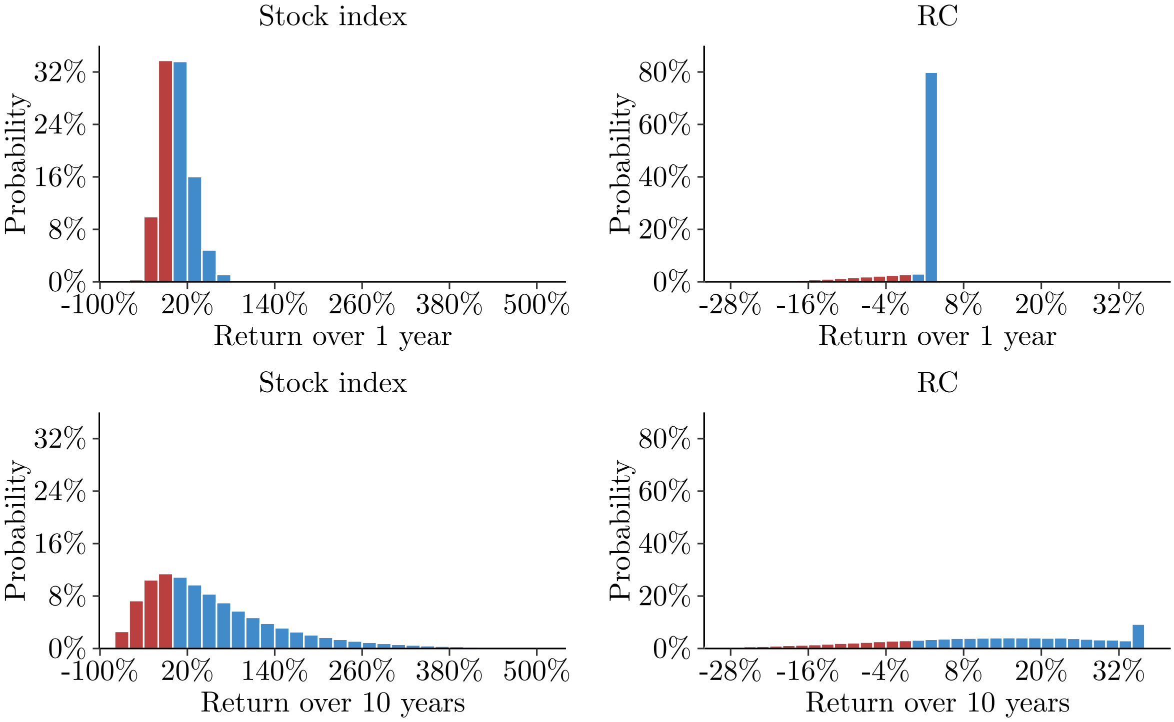
Appendix C

MYOPIC LOSS AVERSION AND STRUCTURED PRODUCT INVESTMENTS

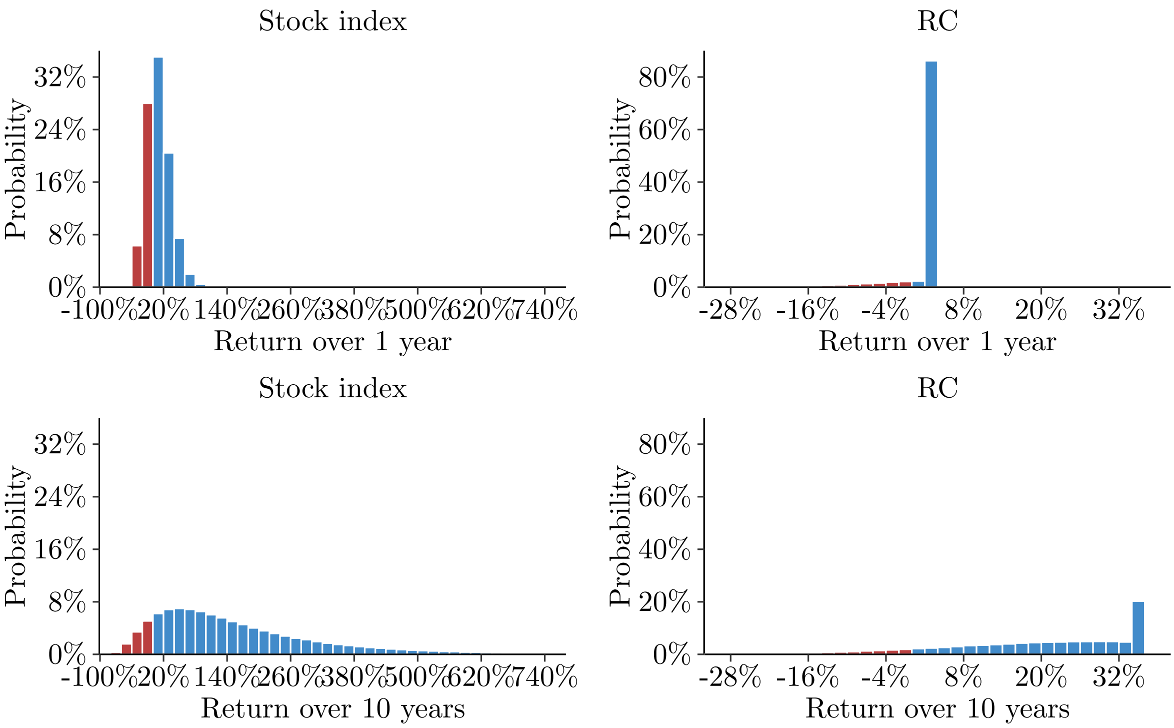
C.1 Return Histograms



Setting 3 ($\mu = 5\%$, $T = 10$)



Setting 4 ($\mu = 10\%$, $T = 10$)



C.2 Overview of Variables and Measures

Dependent Variables

Investment weight stock index. Investment weight of the stock index in the long-term subject group or average investment weight of the stock index in the short-term subject group.

Investment weight RC. Investment weight of the RC in the long-term subject group or average investment weight of the stock index in the short-term subject group.

Treatment Variables

Low frequency. Dummy variable that takes the value 1 if the subject is assigned to the low-frequency group.

Risk Preference Measures

Risk preference measure 1. Ordinal variable that indicates the general risk attitude in investment decisions.

Risk preference measure 2a. Ordinal variable that indicates the likelihood of investing 10% of the annual income in a moderate growth diversified fund.

Risk preference measure 2b. Ordinal variable that indicates the likelihood of investing 5% of the annual income in a very speculative stock.

Risk preference measure 2c. Ordinal variable that indicates the likelihood of investing 10% of the annual income in a new business venture.

Risk preference measure 3a. Certainty equivalent to a lottery with a 60% chance to win 100.

Risk preference measure 3b. 100 deducted by the (absolute value of the) certainty equivalent for a lottery with a 60% chance to lose 100.

Experience Measures

Experience measure 1. Ordinal variable that indicates familiarity with financial assets in general.

Experience measure 2. Ordinal variable that indicates familiarity with derivatives/options or structured financial products.

Experience measure 3. Dummy variable that takes the value 1 if the subject has already invested in stocks, funds or bonds and 0 if not.

Experience measure 4. Dummy variable that takes the value 1 if the subject has already invested in derivatives/options or structured financial products and 0 if not.

Demographic Variables

Age. Age in years.

Education. Ordinal variable that indicates the highest degree.

Gender. Categorical variable that indicates whether the subject is male or female.

Income. Ordinal variable that indicates the monthly net income.

Residence. Categorical variable that indicates where the subject has its residence.

Marital status. Categorical variable that indicates whether the subject is unmarried, married, divorced or widowed.

Profession. Categorical variable that indicates whether the subject is unemployed, in school, employed, self-employed or retired (main activity).

Other Control Variables

Control. Ordinal variable that indicates whether the control questions are answered incorrectly, partially correctly or correctly.

Order. Dummy variable that takes the value 1 if the stock index investment decision(s) is/are taken first and 0 if the RC investment decision(s) is/are taken first.

C.3 Experiment

Instructions

Dear participant,

Welcome to our study on investment decisions.

The study is anonymous, which means that the answers cannot be assigned to the participants at any time. The data will be treated confidentially and used only for research purposes.

The study consists of 2 independent investment stages. In each stage you will receive a hypothetical investment budget of GBP 10 000. You must decide how much of this amount you wish to invest in a financial asset. The financial asset available for investment is different in both stages and will be explained later. The outcome of each stage will be randomly determined by the computer based on the underlying investment decisions.

If you take the investment decisions carefully and if your data is of high quality, you can earn a considerable bonus payment on top of your base compensation. The amount of the bonus payment corresponds to the return achieved at 1 of the 2 investment stages. The standard bonus payment is GBP 2, which you receive in case of a return of 0%. (If the return is, e.g., +10%, the bonus payment is GBP 2 + 10% of 2 = 2.2. And if the return is, e.g., -20%, the bonus payment is GBP 2 - 20% of 2 = 1.6.) The respective investment stage will be picked randomly by the computer.

Many thanks in advance for your participation!

Attention: There is no "back" button.

NEXT

Page 1: First (Block of) Investment Decision(s)

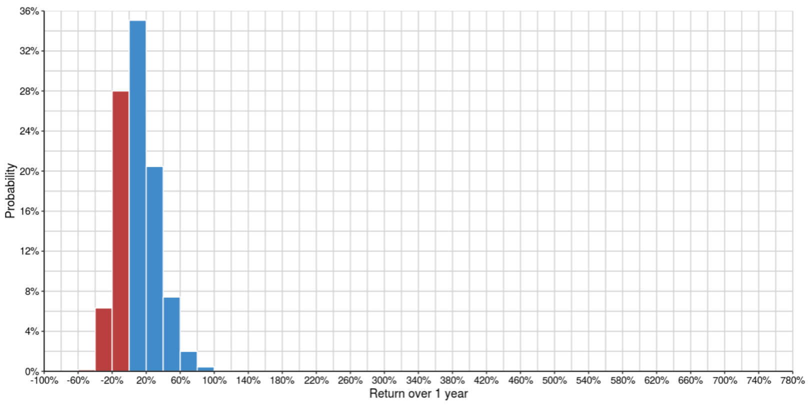
STAGE 1 of 2

Imagine that you start with an investment budget of GBP 10 000, which you can invest for 10 years. You will be asked to (re)allocate your investment budget at the beginning of each year. You can invest in the following financial asset.

Stock index: The stock index consists of a number of shares of different large companies from developed countries. It enables to participate in the profits but also in the losses resulting from these companies. Thus, the value of the stock index can theoretically rise unlimitedly or fall in extreme cases down to zero. However, the risk is spread across a large number of individual companies.

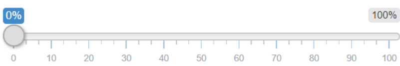
The chart on the right shows the distribution of the profit/loss after investing in the stock index for 1 year. The profit/loss is expressed as a percentage of the investment amount.

The heights of the bars indicate the probabilities that the stock index will have a profit/loss within the range specified on the horizontal axis. (E.g., the probability of achieving a profit between 0% and 20% is roughly 35%.)



What percentage of your investment budget would you like to invest in the stock index in the first year? Use the slider to specify your choice.
Note: The portion that is not invested results in no profit and no loss.

Percentage invested in stock index



INVEST NEXT

Page 1 of 7

Page 2: Control Question

The following statements refer to the stock index of the previous stage. Check the statements that you believe to be true. (You can also check multiple statements.)

- ☐ You can gain more than 10% when investing in the stock index for 10 years.
- ☐ You cannot gain more than 20% when investing in the stock index for 10 years.
- ☐ You can loose more than 10% when investing in the stock index for 10 years.
- ☐ You cannot loose more than 20% when investing in the stock index for 10 years.

NEXT

Page 2 of 7

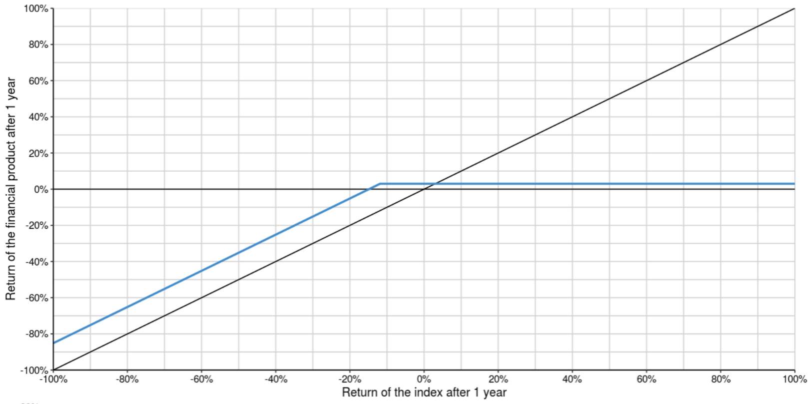
Page 3: Second (Block of) Investment Decision(s)

STAGE 2 of 2

Imagine that you start again with an investment budget of GBP 10 000, which you can (re)allocate at the beginning of each year during the 10-year investment period. However, the financial asset is different now.

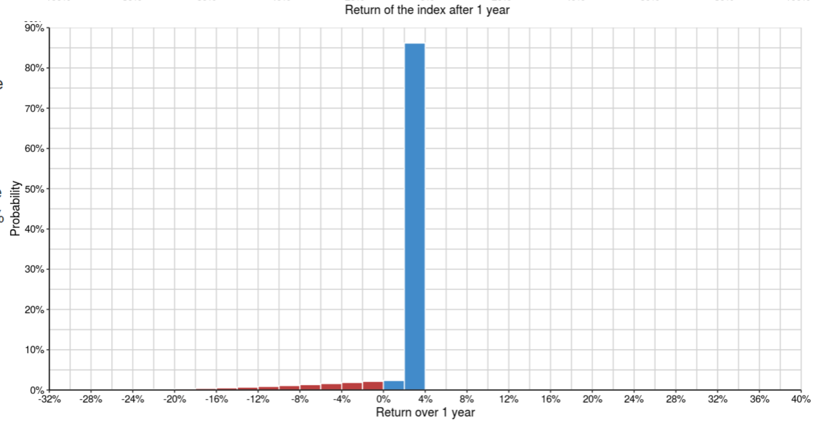
Financial product: The outcome of the financial product is related to a stock index. It corresponds to the profit/loss of the stock index after 1 year plus a premium. However, the profit of the financial product is limited to +3% per year. (Therefore, the financial product performs worse than the stock index in case of a favorable development of the stock index. But it performs better than the stock index in case of an unfavorable development of the stock index.) The stock index itself consists of a number of shares of different large companies from developed countries.

The chart on the right shows the profit or loss of the financial product (vertical axis) as a function of the stock index value after 1 year (horizontal axis). The blue line represents the financial product and the diagonal, black line represents the stock index.



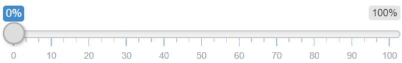
The chart on the right shows the distribution of the profit/loss after investing in the financial product for 1 year. The profit/loss is expressed as a percentage of the investment amount.

The heights of the bars indicate the probabilities that the finacial product will have a profit/loss within the range specified on the horizontal axis. (E.g., the probability of achieving a profit between 0% and 2% is roughly 2.5%.)



What percentage of your investment budget would you like to invest in the financial product in the first year? Use the slider to specify your choice. Note: The portion that is not invested results in no profit and no loss.

Percentage invested in financial product



INVEST NEXT

Page 3 of 7

Page 4: Control Question

What is the highest possible profit when investing in the financial product of the previous stage for 1 year?

- 0%
- 3%
- 100%
- 200%
- The profit is not limited.

NEXT

Page 4 of 7

Page 5: Financial Knowledge and Experience

Finally, we would like to ask you a few questions about yourself.

Are you familiar with financial assets in general?

- Yes, I am very familiar with financial assets.
- I know the basics.
- No, I have never dealt with them.

Are you familiar with derivatives/options or structured financial products?

- Yes, I am very familiar with these assets.
- I know roughly what they are.
- No, I have never dealt with them.

Have you already invested in stocks, funds or bonds?

- Yes
- No

Have you already invested in derivatives/options or structured financial products?

- Yes
- No

NEXT

Page 5 of 7

Page 6: Risk Preferences

How would you assess your risk attitude in a situation where you have to invest GBP 10 000 of your own money?

- Very conservative
- Conservative
- Moderate
- Aggressive
- Very aggressive

For each of the following statements, please indicate the likelihood that you would engage in the described activity or behavior if you were to find yourself in that situation.

Investing 10% of your annual income in a moderate growth diversified fund.

- Extremely unlikely
- Moderately unlikely
- Somewhat unlikely
- Not sure
- Somewhat likely
- Moderately likely
- Extremely likely

Investing 5% of your annual income in a very speculative stock.

- Extremely unlikely
- Moderately unlikely
- Somewhat unlikely
- Not sure
- Somewhat likely
- Moderately likely
- Extremely likely

Investing 10% of your annual income in a new business venture.

- Extremely unlikely
- Moderately unlikely
- Somewhat unlikely
- Not sure
- Somewhat likely
- Moderately likely
- Extremely likely

Imagine you are offered the lottery below.

With a probability of 60% you get GBP 100
and with a probability of 40% you get GBP 0.
Please indicate the maximum amount you are willing to pay to participate in the lottery.

The following lottery includes losses. Imagine you have to participate in the lottery, unless you pay a certain amount before the lottery.

With a probability of 60% you lose GBP 100
and with a probability of 40% you lose GBP 0.
Please indicate the maximum amount you are willing to pay to avoid the lottery.

NEXT

Page 6 of 7

Page 7: Demographics

What is your gender?

- Male
- Female

What is your age?

What is your marital status?

- Unmarried
- Married
- Divorced or separated
- Widowed

Where are you located?

- Africa
- Asia
- Europe
- Middle East
- North America
- Oceania
- South or Central America

What is the highest degree or level of school you have completed? (If you are currently enrolled in school, please indicate the highest degree you have received.)

- No degree
- Elementary school graduation
- High school degree or equivalent
- Bachelor's degree or equivalent
- Master's degree or equivalent
- Doctor's degree or equivalent

Which of the following categories best describes your employment status?

- Unemployed
- Student or in education
- Employed
- Self-employed
- Retired

What is your average monthly net income?

- < GBP 500
- GBP 500 – 1 000
- GBP 1 000 – 2 000
- GBP 2 000 – 3 000
- GBP 3 000 – 5 000
- GBP 5 000 – 10 000
- > GBP 10 000

Please enter your Prolific ID.

24 alphanumeric characters

SUBMIT

Page 7 of 7