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„Behavioral Finance - the Philosopher's Stone?

A Monte Carlo Comparison of Selected

Portfolio Insurance Strategies“

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List of Abbreviations

APT	Arbitrage pricing theory
CAPM	Capital asset pricing model
CPPI	Constant proportion portfolio insurance
CPT	Cumulative prospect theory
EMH	Efficient market hypothesis
EUT	Expected utility theory
LPM	Lower partial moments
MSCI	Morgan Stanley Capital International
NPV	Net present value
RTS	Return to shortfall

List of Symbols

C_t	Market value of the cushion
e(.)	Exponential function
e_t	Market value of the exposure
F_t	Current floor
K	Strike price
k	round-trip transaction costs
ln(.)	Natural logarithm
M	Number of trials
m	CPPI multiplier
max(.)	Maximum function
min(.)	Minimum function
N(.)	Standard normal cumulative distribution
n	Number of observations
n´	Number of observations below the threshold return
p(.)	Cumulative probability
P_t	Premium of the put option
$P(S_0,K)$	Value of the put option

r	Continuously compounded risk-free rate
SE	Standard error
S_t	Market value of the stock price
T	Time to expiration
$v(\Delta x)$	Value function cumulative prospect theory
W_t	Market value of the portfolio
w_t	Portfolio proportions in the risky asset
z	Protection level in percent
z_t	Wiener process
$\sqrt{.}$	Square root
$\sum .$	Sum operator
α	Sensitivity towards gains
β	Sensitivity towards losses
γ	Discriminability coefficient
δ	Attractiveness coefficient
Δt	Length of the time interval
Δx	Deviation from the reference point
λ	Loss aversion coefficient
μ	Drift of continuously compounded stock returns
π	Threshold return
π_i	Decision weight of the outcome i
σ	Standard deviation of continuously compounded stock returns

1. Introduction

In the past two decades, financial markets experienced, figuratively speaking, a roller coaster ride which cannot be explained by traditional finance theory: seasons of high performance alternated with seasons where the market went to a drastic free-fall, equity prices significantly differed from its fundamental values, bubbles formed and busted, investors behaved irrational by purchasing overvalued titles and selling undervalued ones. Traditional finance theory with its emphasis on rationality seems not to hold any more. Fox (2009, p. 308) even goes so far to claim that *„the rational market theories have fallen apart"*. Do the traditional elements of finance as homo oeconomicus, expected utility theory (EUT) (Neumann & Morgenstern, 1944) and traditional finance models, such as the efficient market hypothesis (EMH) (Fama, 1970), the mean variance portfolio (Markowitz, 1952), the capital asset pricing model (CAPM) (Lindtner, 1965; Mossin, 1966; Sharpe, 1964) and the arbitrage pricing theory (APT) (Ross, 1976) really have difficulties to explain the recent market situation properly? This should not be big news since various empirical studies conducted in the 1980´s revealed that the market is not that efficient as explained by EMH. Prominent examples are the equity premium puzzle (Mehra & Prescott, 1985), calendar effects (Rozeff & Kinney, 1976; Tinic & West, 1984; Lakonishok & Smith, 1987; Cross, 1973), size effects (Banz, 1981; Fama & French, 1992), short-term momentum (Jegadeesh & Titman, 1993; Rouwenhorst, 1998) and long term reversals (De Bondt & Thaler, 1985; Chopra et al., 1992). However, supporters of the EMH argue that, in the long run, equity prices experience mean reversion as they return to their fundamental values and simply called the empirically observed deviations from EMH anomalies that only occur in an unsystematic manner.

But what if these "anomalies" are the rule rather than the exception? There is irrationality in the market – not only in the last few years which are certainly characterized by the subprime lending crises but also in the last two decades, at least. Several market crashes as the Black Monday in 1987, the dot.com bubble of the late 1990´s and the recent subprime lending crisis starting out in 2007 are perhaps no anomalies any more. Regarding that almost all elements of traditional finance theory were developed between 1952 and 1973 (Bernstein, 2007, p. 1), it seems that something has changed since Markowitz, Fama, Sharpe, Lindtner, Mossin and Ross formulated their models based on rationality. Since the 1980´s, financial markets went through a drastic change due to the liberalization of capital markets, the appearance of financial innovation (most prominent derivatives and portfolio insurance strategies) and improvements made in information technology. New markets were created in which options and futures were traded, thereby facilitating the implementation of portfolio insurance strategies. Such strategies, that provide protection against losses in adverse states while preserving some upward potential in good states, seem to be attractive for a wide range of investors, especially in the light of the turbulent stock market behavior of the recent past. However, traditional finance theory still struggles to provide an explanation for their widespread demand. Since portfolio insurance strategies yield lower returns than a passive stock market investment, Dreher (1988) even raises the question if portfolio insurance strategies can ever make sense as taking over systematic risk is rewarded with an equity premium. Cesari and Cremonini (2003) document that the relative performance of portfolio insurance strategies depends on the respective market phase whereas Bird et al. (1990) indicate that portfolio insurance strategies are robust in various market phases, including stock market crashes. Annaert et al. (2009) find that, despite of the lower return potential, the reduced downside risk make them attractive at least for some investors. However, within the traditional finance framework based on rationality no clear evidence for the popularity of portfolio insurance strategies can be found. As a vast amount of research suggests, investors do not always behave rationally when forming their preferences and systematically fail to update their beliefs correctly. Smith and Harvey (2011, p. 65) argue that investors are not doing the requisite amount of research and are more and more influenced by the media, making choices on what they see and hear rather than conducting fundamental analysis. Yang and Lester (2008, p. 1) even claim that rationality might be the exception rather than the norm. If this is the case, then maybe the new behavioral models can serve to understand market reactions better than the traditional models based on rational behavior.

Therefore, the overriding objective of this thesis is to explain the unbroken popularity of portfolio insurance strategies in a behavioral finance context. Since Benninga and Blume (1985, p. 1345) find that the optimality of a portfolio insurance strategy depends on the investor´s utility function and Polkovnichenko (2005, p. 1499) calls for rank-dependent utility function when examining portfolio insurance strategies, a selective choice of prominent portfolio insurance strategies together with simple benchmark strategies are analyzed within the framework of Tversky and Kahneman´s (1992) cumulative prospect theory (CPT). More precisely, four portfolio insurance strategies will be examined: the stop-loss portfolio insurance strategy, the protective put portfolio insurance strategy, the synthetic put portfolio insurance strategy and the constant proportion portfolio insurance (CPPI) while the pure stocks investment, the pure cash investment and the 50%-50% buy and hold investment serve as benchmark strategies. Following the work of Dichtl and Drobetz (2010), Monte Carlo simulations generate continuously compounded stock market returns following a Geometric Brownian motion whereas the input parameters are derived from the historical data of the MSCI Europe, MSCI USA and MSCI World total return indices over the period from January, 1980 to December, 2011. Then, the various portfolio insurance strategies are applied and the corresponding CPT values are computed. Finally, an extensive sensitivity analysis reveals additional insights into the optimal design of a portfolio insurance, at least from the standpoint of an investor with prospect theory preferences[1].

The remainder of this thesis is structured as follows: Section 2 discusses the elements of behavioral finance and describes the functional forms applied. Section 3 provides a brief description of the portfolio insurance strategies selected. Section 4 discusses the Monte Carlo simulations, thereby explaining the simulation setup, evaluating the base case results and further examining the results of the sensitivity analysis. Section 5 concludes and raises the issue for the need of future research regarding some limitations of this work.

2. Behavioral Finance

The theory of behavioral finance originated in the early 1950´s (Shefrin & Statman, 1984) and is mainly based on the two pillars of limits of arbitrage and investor psychology (Shleifer & Summers, 1990).

2.1 Limits of arbitrage and psychology

According to behavioral finance, strategies designed to exploit the mispricing of securities might not always be worth executing since they involve high risk or high costs, respectively (limits of arbitrage). The inherent risk might be either fundamental, when arbitrageurs fail to find perfect substitutes for their hedging programs or they face the

[1] The work of Dichtl and Drobetz (2010) serves as a guideline since their paper on the popularity and optimal design of portfolio insurance strategies was the motivation for this thesis.

problem that the undervalued security bought decreases even further in value (noise trader risk) (Barberis & Thaler, 2005, p. 5). Besides, real world transaction costs might impose constraints on arbitrageurs as well, allowing deviations from the fundamental values to persist. Additionally, investors fail to update their beliefs correctly or rely on heuristics rather than rational behavior, leading to certain systematic biases. According to Barberis and Thaler (2005, p. 12 – 16), investors tend to have unrealistic positive views of their abilities and overestimate their own expertise (overconfidence), they rely on stereotypes (representativeness), hold on to their initial beliefs and are reluctant to update them (belief perseverance). When estimating probabilities, investors choose an initial starting point and then adjust away from it (anchoring and adjustment), frequently fail to consider the entire sample size (representativeness) and rely on more recent or more salient information (availability).

Since investors beliefs are biased in so many ways, the decisive question arises if, once aware of these cognitive errors, investors might learn avoiding them. However, since the empirically observed “anomalies” are not isolated incidences but repeated occurrences[2], it seems that, although some investors might be learning from their intuitive errors, others are not. But how do these biases influence investors´ financial decisions or more precisely, their decisions on how to allocate their financial funds?

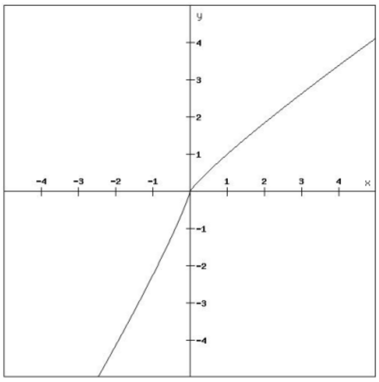
2.2 Cumulative Prospect theory

Performing several experiments, Kahneman and Tversky (1979) found that investors do not always behave rationally when forming their preferences. They define their utility over gains and losses relative to some reference point – usually the status quo (Benartzi & Thaler, 1995, p. 74) which is known as framing (Kahneman & Tversky, 1981). They are risk-averse in the domain of gains but risk-takers when facing losses which implies an s-shaped utility function that is kinked at the reference point (Figure 1). Besides, investors tend to weight losses more extreme than an equivalent amount of gains which reflects loss aversion. Also, investors tend to overweight the probability of extreme but less likely events and to underweight the probability of events which are

[2] A tremendous amount of empirical studies has already been conducted within this field. See Shefrin (2002) and Thaler (2005) who provide an extensive summary of the empirical research. Moreover, see Shefrin´s (2007) work on how human traits influence corporate finance.

more likely. Consequently, such behavior leads to distorted decision weights that nonlinearly depend on the statistical probabilities.

Figure 1: S-shaped utility function assumed by CPT



Further experiments conducted by Tversky and Kahneman (1992) revealed that the impact of a change in outcome diminishes with the distance to the reference point (diminishing sensitivity) and that investors care more than twice as much about potential losses than about potential gains. Diminishing sensitivity also holds true for the probability weighting function as investors are more sensitive to differences in probabilities that are near 0 and 1 (certainty effect).

Therefore, Tversky and Kahneman (1992) suggest that the investor´s value function v(Δx) is defined on deviations from a reference point Δx, being concave for gains (implying risk-aversion) while convex for losses (implying risk-seeking) as well as being steeper for losses than for gains.

Equation 1: Two-part valuation function

$$v(\Delta x) = \begin{cases} (\Delta x)^{\alpha} & \Delta x \geq 0 \\ -\lambda\,(-\Delta x)^{\beta} & \Delta x < 0 \end{cases}$$

where α ≈ β ≈ 0.88 reflect the sensitivity towards gains and losses and λ≈ 2.25 denotes the loss aversion coefficient based on their empirical results.

The probability weighting function, on the other hand, puts extra weights on the tails of the return distribution, thereby accounting for overestimating low probability events (attractiveness) and the sensitivity towards changes in probabilities (discriminability). In accordance to that, Lattimore et al. (1992) suggest the following probability weighting function (Equation 2), whereas γ mainly controls discriminability, δ mainly controls attractiveness and p denotes the cumulative probabilities[3].

Equation 2: Probability weighting function

$$w_{\delta,\gamma} = \begin{cases} w^{+}(p) = \dfrac{\delta^{+} \cdot p^{+}}{\delta^{+} \cdot p^{+} + (1-p)^{\gamma^{+}}} & \Delta x \geq 0 \\ w^{-}(p) = \dfrac{\delta^{-} \cdot p^{-}}{\delta^{-} \cdot p^{-} + (1-p)^{\gamma^{-}}} & \Delta x < 0 \end{cases}$$

with $\delta^+ = 0.65$, $\delta^- = 0.84$, $\gamma^+ = 0.6$ and $\gamma^- = 0.65$ based on the empirical results of Abdellaoui (2000).

In avoidance of first-order stochastic dominance violations[4], the decision weights π_i have to be calculated stepwise. First, to ensure monotonicity, the outcomes Δx_i (representing gains and losses relative to the reference point) have to be ranked in ascending order. Second, the cumulative probabilities are weighted according to Equation 2. And third, the differences of neighboring cumulative probabilities are computed according to Equation 3. Therefore, the decision weight associated with a positive outcome is the difference between the weighted probabilities of the events “the outcome is at least as good as Δx_i” and “the outcome is strictly better than Δx_i” whereas the decision weight associated with a negative outcome is the difference between the

[3] Dierkes et al. (2010) examine the attractiveness of portfolio insurance strategies with the probability weighting function suggested by Tversky and Kahneman (1992). However, Ingersoll (2008) claims that this function leads to potential violations of first-order stochastic dominance when the parameters are unconstrained. Also, Abdellaoui (2000) finds that the function suggested by Lattimore et al. (1992) provides a better separation between gains and losses.

[4] The original version of prospect theory (Kahneman & Tversky, 1979) suffered from potential violations of first order dominance. This shortcoming is corrected with the weighting of cumulative probabilities instead of single ones (Tversky & Kahneman, 1992).

weighted probabilities of the events "the outcome is at least as bad as Δx_i" and "the outcome is strictly worse than Δx_i" (Tversky & Kahneman, 1992).

Equation 3: Decision weights

$$\pi_i = \begin{cases} \pi_i^- = w^-(p_1 + \cdots + p_i) - w^-(p_1 + \cdots + p_{i-1}) & \Delta x < 0 \\ \pi_i^+ = w^+(p_i + \cdots + p_n) - w^+(p_{i+1} + \cdots + p_n) & \Delta x \geq 0 \end{cases}$$

where π_i denotes the decision weights and i the outcomes Δx_i (with i = 1,…,n). Consequently, an investor with CPT preferences evaluates his financial decisions based on the following utility function.

Equation 4: CPT value

$$CPT(Strategy) = \sum_{i=1}^{n} \pi_i \cdot v(\Delta x_i)$$

In section 4, the analysis of the selected portfolio insurance strategies and the respective benchmark strategies is based on the corresponding CPT values according to Equation 1 to Equation 4 in order to examine which investment strategy is the most attractive one in a CPT investor´s point of view[5]. In order to test the attractiveness of different portfolio insurance methodologies, the analysis consists of two static portfolio insurance strategies and two dynamic portfolio insurance strategies, respectively. The following section briefly describes the differences between static and dynamically adjusted portfolio insurance strategies and then proceeds with a more detailed description of each portfolio insurance strategy selected.

[5] Dichtl and Drobetz (2010) also examine the portfolio insurance strategies with λ =1 (no loss aversion) and λ = 2.25, respectively, omitting probability weighting. They find that loss aversion alone is only one explanation for the attractiveness of portfolio insurance strategies and that the probability weighting scheme further contributes to their attractiveness. Moreover, Dierkes et al. (2010) conclude that the probability weighting scheme is the decisive factor for the attractiveness of portfolio insurance strategies.

3. Portfolio insurance strategies

The main idea of portfolio insurance strategies is to provide protection against losses through a pre-specified floor while simultaneously offering participation from upward stock market movements. Hence, portfolio insurance strategies aim to reshape the return distribution in such a way that they cut off its negative tail, resulting in an asymmetric return distribution that is skewed towards positive returns. However, this comes at a cost as the maximum return potential of insured portfolios is lower than that of uninsured ones. This is particularly true for option based portfolio insurance strategies (Steiner et al., 2012, p. 393).

In the early 1980s, portfolio insurance strategies gained momentum with the introduction of the synthetic put strategy (Rubinstein & Leland, 1981) and with the further development of new portfolio insurance strategies soon reached its climax in 1987. After that, portfolio insurance strategies repeatedly came under pressure, especially since they were blamed to cause the stock market crash in October, 1987. Critics accuse the trading pattern of portfolio insurance strategies to amplify swings in market prices since they systematically sell stocks as prices fall and buy stocks as prices rise[6]. However, during the crash, portfolio insurance strategies only accounted for 2% of total US equity market capitalization whereas stock sales due to portfolio insurance only accounted for 0.2% of total US equity market capitalization (Leland & Rubinstein, 1988, pp. 48 - 49). Therefore, it seems unlikely that portfolio insurance alone might have triggered the drastic price slide at that point in time (Aschinger, 1992, p. 24). Nonetheless, the crash in October, 1987, helped to reveal some weak points of portfolio insurance strategies, with the side effect of inducing investors to evaluate potential risks more realistic, to employ portfolio insurance more conservative and to use traded options again (Albrecht & Maurer, 1992, p. 339).

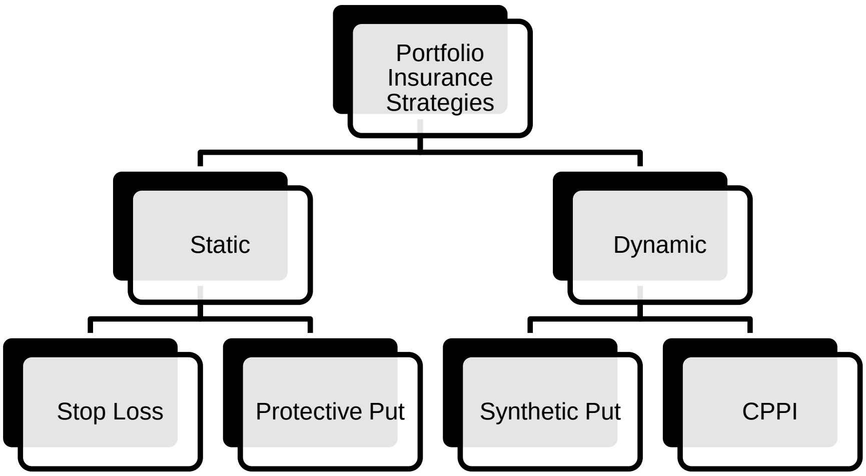
Although the implementation of portfolio insurance strategies provides a reduced return potential, it seems that portfolio insurance strategies might be attractive for a wide range of investors and should be particularly attractive for CPT investors, since their

[6] In order to avoid reinforcing trends which might be triggered through the implementation of portfolio insurance strategies, Leland (1980, p. 581) suggests that high order volumes should be revealed to the market before the order is even entered (sunshine trading).

response to a loss is more extreme than their response to a gain. However, the decisive question is which portfolio insurance strategy is the most attractive for a CPT investor?

The diversity of portfolio insurance strategies allows protecting a risky portfolio from negative market movements in numerous ways that can be either static or dynamic. Figure 2 shows the most prominent portfolio insurance strategies which are selected for the Monte Carlo simulation analysis in section 4.

Figure 2: Selected portfolio insurance strategies



Static portfolio insurance strategies are characterized by the maintenance of the initially selected asset allocation throughout the investment horizon or the originally selected asset allocation is only changed once, respectively (Steiner et al., 2012, p. 394). Thus, static portfolio insurance strategies can be regarded as buy and hold strategies where the investment in the risky asset has either a time limit (protective put) or is tied to a pre-specified stock price level (stop loss) (Kluß et al., 2005, p. 7). In contrast, within dynamic portfolio insurance strategies the asset allocation has to be continuously adjusted during the investment horizon in response to a changing stock market environment. Hence, if the value of the risky asset is increasing in regards to the risk-free asset, a greater proportion of the portfolio is invested in the risky asset at the expense of the risk-less asset and vice versa. Consequently, the trading pattern of portfolio insurance strategies contrasts the fundamental rule “sell high, buy low” which might reinforcing market trends (Steiner et al., 2012, p. 410).

Besides, portfolio insurance strategies can be either path dependent or path independent. If the terminal portfolio value depends only on the terminal stock market price, then the portfolio insurance strategy is path independent (protective put[7]) but if the terminal portfolio value depends on interim stock market movements as well, then the portfolio insurance strategy is path dependent (stop loss and dynamic portfolio insurance strategies) (Steiner et al., 2012, p. 395).

3.1 Stop loss portfolio insurance strategy

The stop loss strategy is easy to implement and does not require any specific assumptions nor any model parameters (Dichtl & Drobetz, 2010, p. 1684). Within this strategy, the investor´s initial total wealth W_0 is invested in the risky asset and as long as the market value of the portfolio W_t doesn´t reach or drop below the net present value (NPV) of the current floor F_t, this position is maintained.

Equation 5: Stop-loss portfolio insurance strategy

$$W_t > NPV\ (F_t)$$

When the current market value of the portfolio reaches or drops below the NPV of the current floor, all holdings in the risky asset are liquidated and invested in the risk-free asset. This position is held until the end of the investment horizon which means that the investor cannot participate from any upward market movement any more, even when the risky assets sharply recovers afterwards[8].

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[7] When the investment horizon is longer than the option maturity, the short-term puts have to be rolled over as they mature which makes the rolling protective put strategy path dependent (Figlewski et al., 1993, p. 47).

[8] The modified stop loss strategy (Bird et al., 1988) as well as the multi-point stop loss strategy (Bookstaber, 1985) provide an alternative approach which allows for a participation in an upward market movement after the floor has been breached.

3.2 Protective put portfolio insurance strategy

The protective put strategy, on the other hand, involves buying traded put options in order to protect the underlying portfolio value from negative market movements. Since buying the put itself is costly, the minimum guaranteed terminal portfolio value equals the strike price K minus the put´s option premium P_t and the transaction costs (Steiner et al., 2012, p. 396). If the terminal portfolio value at the put´s maturity is less than the strike price, the put option will be exercised, leading to a cash inflow equal to the amount the put is in the money and thereby compensates for the loss in the stock position[9]. On the contrary, if the terminal portfolio value at the put´s maturity is greater than the strike price, the put will not be exercised since it is worthless. Thus, the protective put insurance strategy offers unlimited upside potential while simultaneously guaranteeing a pre-specified floor. However, the upside potential of the protective put strategy will always be lower than that of a pure stock investment since it initially involves buying the put premium.

Besides, the choice of the strike price crucially influences the terminal return of the investment strategy since higher protection levels result in a lower upside potential as buying the put is more costly[10]. Although choosing a strike price equal to the initial portfolio value and the put premium guarantees the protection of the investor´s entire initial wealth, the protective put insurance policy usually involves buying at the money or slightly out of the money put options (Dierkes et al., 2010, p. 1035). Another important determinant of the protective put portfolio insurance strategy is the time to expiration. Generally, the protective put strategy involves buying short-term puts which have to be rolled-over at expiration (rolling hedge). Buying short-term puts is more costly than buying longer-lived puts since it is more valuable having the right to sell the stock sooner than later[11]. Also, a higher portfolio turnover leads to higher transaction costs. However, Figlewski et al. (1993, p. 50) finds that the cost of a one-month rolling hedge over the period of a year is far less than twelve times the one month costs.

[9] This holds true for European options since they can be exercised only on the expiration date whereas American options can be exercised at any time up to the expiration date.

[10] Since it is more valuable having the right to sell a stock at a higher price, the put premium will be more costly the higher the strike price and vice versa.

[11] This, again, holds only true for European options since American options can be exercised any time up to the expiration date.

Nevertheless, the implementation of the protective put strategy can be rather problematic since it requires tradable European put options which may not be available with the appropriate strike price and time to expiration, respectively (Steiner et al., 2012, p. 399).

3.3 Synthetic put portfolio insurance strategy

In order to avoid these shortcomings, the put option can be replicated by dynamically shifting between the risky asset and the risk-free asset, thereby creating a continuously adjusted synthetic European put option on the stock (Rubinstein & Leland, 1981). Based on the option pricing formula of Black and Scholes (1973), the put´s option premium is given by

Equation 6: Black and Scholes put option premium

$$P_t = -S_t\, N(-d_1) + Ke^{-rT}N(-d_2)$$

where K denotes the strike price, r the annual continuously compounded risk-free rate, T the time to expiration and N(.) is the standard normal cumulative distribution function with d_1 and d_2

Equation 7: Standard normal cumulative distribution function, d_1 and d_2

$$d_1(S_t) = \frac{\ln\left(\frac{S_t}{K}\right) + \left(r + \frac{\sigma^2}{2}\right)T}{\sigma\sqrt{T}}$$

$$d_2(S_t) = d_1 - \sigma\sqrt{T}$$

where σ is the annual standard deviation of the continuously compounded stock returns. Since the protective put strategy involves the purchase of a stock S_t and the corresponding put P_t which is priced according to Equation 6, the value of the replicating portfolio can be rewritten as (Benninga, 2008, p. 579)

Equation 8: Replicating portfolio value synthetic put

$$\begin{aligned} S_t + P_t &= S_t - S_t\, N(-d_1) + K\, e^{-rT}\, N(-d_2) \\ &= S_t\, [1 - N(-d_1)] + Ke^{-rT}\, N(-d_2) \\ &= S_t\, N(d_1) + Ke^{-rT}\, N(-d_2) \end{aligned}$$

thereby substituting the put premium P_t with Equation 6. Consequently, the put option on a stock is equivalent with a portfolio consisting of a short position in the stock and a long position in the risk-free asset.

Since the synthetic put portfolio insurance strategy requires a continuously adjustment of the positions in the stock w_t and the risk-free asset (1 - w_t) in response to the stock price movements, Equation 8 has to be rearranged in regards to the respective portfolio proportions.

Equation 9: Portfolio weights synthetic put

$$w_t = \frac{S_t}{S_t + P_t}$$

$$w_t = \frac{S_t\, N(d_1)}{S_t\, N(d_1) + Ke^{-rT} N(-d_2)}$$

According to the synthetic put strategy, the proportion of the stock investment is increasing as the stock price increases and is decreasing as the stock prices decreases.

Since each portfolio adjustment involves transaction costs, Boyle and Vorst (1992) suggest a modified volatility estimator for the put´s option premium[12]

Equation 10: Modified volatility estimator

$$\sigma_{Boyle/Vorst} = \sigma \sqrt{1 + 2 \cdot \frac{k}{\sigma \sqrt{\Delta t}}}$$

where k denotes the round-trip transaction costs and Δt the length of the rebalancing interval.

In order to guarantee a certain protection level z of the investor´s initial wealth, the strike price K has to be derived iteratively since the value of the put option $P(S_0,K)$ depends on the strike price itself[13] (Benninga, 2008, pp. 588 - 591).

Equation 11: Strike price for a specific protection level

$$K = z \cdot (S_0 + P(S_0, K)$$

where z denotes the protection level in percent.

Basically, the choice of the protection level has the same implications on the terminal return as within the protective put portfolio insurance policy: the higher the floor, the lower the resulting return of the strategy. The choice of the time to expiration, or more

[12] Leland (1985) also suggests a modified volatility estimator to capture the transaction costs whereas $\sigma_{Leland} = \sigma \sqrt{1 + \sqrt{\frac{2}{\pi}} \cdot \frac{k}{\sigma \sqrt{\Delta t}}}$. However, the formula provided by Boyle and Vorst (1992) leads to higher option values which may be more accurate since underestimating the volatility has crucial implications on the synthetic put´s protection level.

[13] Besides, the strike price will be greater than the protected floor since the put is costly.

precisely, the frequency of the rebalancing interval, however, has far-reaching consequences. The synthetic put strategy is based on the assumptions of the Black and Scholes (1973) option pricing model which assumes continuously portfolio adjustments. Although this is not feasible in practice, the portfolio has to be rebalanced as frequently as possible in order to keep potential replication errors within limits. Frequently rebalancing, on the other hand, involves higher transaction costs. Thus, the investor faces the dilemma of a trade-off between reliability and lower transaction costs. Additionally, at the end of the investment horizon, the portfolio will either consist of stocks only (if the synthetic put expires in the money) or of the risk-free asset only (if the synthetic put expires out of the money) (Benninga, 1990, p. 21). This is particularly important for multi-period portfolio insurance strategies as, at the end of each period, the portfolio has to be completely reallocated which might entail substantial transaction costs[14] (Black & Rouhani, 1989, p. 701). Moreover, the quality of the synthetic put strategy crucially depends on the estimation of the standard deviation since underestimating the volatility of the stock results in a lower protection level than desired and vice versa (Rendleman & O´Brian, 1990, p. 61).

3.4 Constant proportion portfolio insurance strategy

To bypass the associated problems with the Black and Scholes (1973) option pricing model, the portfolio adjustments between the risky asset and the risk-free asset can be implemented based on the CPPI portfolio insurance strategy (Black & Jones, 1987; 1988; Perold, 1986). Consequently, the CPPI portfolio insurance strategy guarantees a pre-specified floor while preserving the upside potential by dynamically shifting between the stock and the risk-free asset. In contrast to the previous portfolio insurance strategies, the CPPI portfolio strategy provides a cushion to the risky asset which is adjusted by a multiplier m, whereas the cushion C_t represents the difference between the current wealth W_t and the NPV of the floor F_t.

Equation 12: Cushion CPPI portfolio insurance

$$C_t = W_t - NPV(F_t)$$

[14] This holds also true for the stop loss portfolio insurance if the portfolio ends up fully invested in the risk-free asset.

The proportion of the portfolio allocated to the risky asset (exposure e_t) is computed by multiplying the cushion C_t with the respective multiplier m

Equation 13: Exposure CPPI portfolio insurance

$$e_t = m \cdot C_t$$

whereas the remainder of the portfolio is allocated to the risk-free asset. Besides, the multiplier determines the aggressiveness of the strategy since the inverse of the multiplier indicates the maximum sudden loss in the risky asset that may occur without violating the NPV of the floor (Zimmerer & Meyer, 2006, p. 12). Therefore, the multiplier has to be set such that it incorporates the degree of the investor´s loss-aversion[15].

Usually, the CPPI portfolio insurance strategy is implemented with a no-short-sales and leverage constraint (Benninga, 1990, p. 22). To be consistent with this methodology, the exposure e_t in Equation 13 has to be modified.

Equation 14: Modified exposure CPPI portfolio insurance

$$e_t = max\ [\ min\ (m \cdot\ C_t, W_t), 0\ ]$$

Hence, the CPPI portfolio insurance strategy is fairly simple to implement compared to the synthetic put portfolio insurance strategy and does not depend on estimates such as the standard deviation (with exception of the multiplier[16]). Additionally, at the end of the investment horizon, the portfolio consists of both, stocks and the risk-free asset, thereby avoiding the shortcomings of drastic portfolio reallocations in multi-period

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[15] Hocquard et al. (2012, p. 6) suggest a time-variant multiplier, whereas $m_t = W_t \cdot \frac{e_t}{(W_t - Fe^{-rT})}$. I recognize that this may be a better estimate but to be consistent with Dichtl and Drobetz (2010), m remains fixed at an arbitrarily chosen level.

[16] However, if the multiplier is calculated as suggested by Hocquard et al. (2012), the CPPI strategy depends on observable parameters only.

portfolio insurance strategies. However, the choice of the protection level and rebalancing frequency is as important as it is for the synthetic put portfolio insurance strategy. Additionally, frequent rebalancing also reduces the risk that a sudden loss might occur which violates the NPV of the floor. Because if the stock price exhibits a sudden loss greater than the inverse of the multiplier, the terminal value of the portfolio will drop below the desired floor, even if the allocation to the risk-free asset was executed immediately (gambler´s ruin) (Zimmerer & Meyer, 2006, p. 12). But even if the portfolio is monitored on a daily basis, the risk of extreme market losses still exists overnight (overnight risk) which can be partly controlled by choosing an appropriate multiplier (Dichtl & Drobetz, 2010, p. 1685). However, a higher rebalancing interval evolves higher transaction costs which are particular pronounced in high volatility states without clear upward or downward trends (Steiner et al., 2012, p. 408). In order to avoid a high turnover which is triggered by trendless markets, the CPPI portfolio insurance strategy is usually implemented with a trading filter.

4. Simulation analysis

Hence, portfolio insurance strategies aim to protect the investor’s wealth through a pre-specified protection level while simultaneously preserving some upward potential from positive market movements. Although each one has its limitations, it seems that portfolio insurance strategies are an attractive tool for a wide range of investors. The decisive question is, however, if portfolio insurance strategies are an attractive tool for a CPT investor and if so, which one is designed in such a way that it meets the CPT investor´s preferences as accurately as possible?

For answering this very issue, a Monte Carlo simulation approach is conducted, incorporating all portfolio insurance strategies presented in section 3 and comparing them to widespread implemented benchmark strategies such as a pure investment in a stock, a pure investment in the risk-free asset (cash) and a 50%-50% buy and hold investment in the stock and the risk-free asset, respectively.

Most studies that analyze portfolio insurance strategies are based on Monte Carlo simulations that generate continuously compounded stock market returns on the basis of a Geometric Brownian motion (Figlewski et al., 1993; Benninga, 1990; Dichtl & Drobetz, 2010). Although the time series properties of real world stock prices such as autocorrelation, skewness and fat tails are neglected, Monte Carlo simulations provide a good illustration of the impact of changing stock market behavior to portfolio values. Moreover, the typical behavior of portfolio insurance strategies under normal (high probability) and unusual (low probability) events can be examined, whereas performance analysis based on historical data is limited to one single run of history[17] (Figlewski et al., 1993, p. 47).

4.1 Simulation design

Therefore, the Monte Carlo simulations generate random stock prices on the basis of a Geometric Brownian motion with an annual drift μ and an annual volatility σ, where z_t represents a Wiener process describing the evolution of a normally distributed variable with a mean of 0 and a volatility of 1 (Benninga, 1990, p. 492)[18].

Equation 15: Calculation of stock prices based on a Geometric Brownian motion

$$S_{t+\Delta t} = S_t \, e^{(\mu\Delta t + \sigma\sqrt{\Delta t} * z_t)}$$

Under this stochastic process, the continuously compounded return of a stock is normally distributed whereas the stock price itself has a lognormal distribution (Hull, 2008, p. 275). This assumption is also consistent with the Black and Scholes (1973) option pricing model which is used for the evaluation of both, the synthetic put and the protective put portfolio insurance strategy.

[17] A single run of history could be either typical or unusual which makes it difficult to derive generalized conclusions.

[18] Since the Monte Carlo simulations are done on behalf of VBA EXCEL programming routines, the standard normal random numbers are generated with the VBA code suggested by Lai et al. (2010, pp. 114 - 116) based on the Box-Muller algorithm (Box & Muller, 1958). Benninga (2008, pp. 760 - 762) also suggests to generate random distributed normal deviates with the Box-Muller algorithm, but uses a slightly different VBA code.

In order to derive the full distribution of outcomes, the Monte Carlo simulations generate 100.000 random paths for daily stock prices over a period of one year. The initial stock price S_0 is set at 100 and the subsequent 250 stock prices are generated randomly with an annual drift μ and volatility σ, using Equation 15. Since broad market indices allow for better diversification, μ and σ are calculated on behalf of daily historical financial markets data[19] of the total return indices MSCI Europe, MSCI USA and MSCI World over the period from January, 1980 to December, 2011, respectively[20].

When the continuously compounded return is normally distributed, the simple return has a lognormal distribution (Hull, 2008, p. 282). Since most investors evaluate their portfolios on an annual basis (Benartzi & Thaler, 1995, p. 83), the annual simple mean return and its standard deviation in the lognormal case are (Figlewski et al., 1993, p. 69)

Equation 16: Annualized simple mean return and standard deviation

$$Annual\ simple\ mean\ return\ =\ e^{\left(\mu+\frac{\sigma^2}{2}\right)}-1$$

$$Annual\ standard\ deviation\ \ simple\ return\ =\ e^{\mu}\sqrt{e^{\sigma^2}-1}$$

Table 1 depicts the results for the historical annual mean and volatility as well as the simulated annual mean and volatility and their respective theoretical values according to Equation 16. The results of the Monte Carlo simulations are quite close to the theoretical values, indicating that the Monte Carlo simulations provide an adequate degree of accuracy[21].

[19] Assuming n observation dates and 250 trading days a year, the calculations are as follows $r_t = \ln\left(\frac{S_t}{S_{t-1}}\right)$, $\mu_t = \frac{1}{n}\sum_{i=1}^{n} r_t$, $\mu_{p.a.} = \mu_t \cdot 250$, $\sigma_t = \sqrt{\frac{1}{n-1}\sum_{i=1}^{n}(r_t - \mu_t)^2}$ and $\sigma_{p.a.} = \sigma_t \cdot \sqrt{250}$ (Benninga, 2008, p. 489).

[20] All data is taken from Thompson Reuters Datastream.

[21] Beyond that, the accuracy of the simulation results is as well ensured by the insignificantly small standard errors of the Monte Carlo simulations (see section 4.3).

Table 1: Historical annual mean and volatility vs. Monte Carlo simulation values

	Historical data		Monte Carlo simulation			
	Annual mean return continuously compounded	Annual volatility continuously compounded	Sample annual mean simple return	Theoretical annual mean simple return	Sample annual volatility simple return	Theoretical annual volatility simple return
MSCI Europe	9,66%	19,41%	12,24%	12,23%	22,00%	21,59%
MSCI USA	10,05%	17,74%	12,33%	12,32%	20,09%	19,77%
MSCI World	9,09%	15,88%	10,91%	10,90%	17,73%	17,50%

Then, for each simulation run, the various portfolio insurance strategies are applied. Since all portfolio insurance strategies are rebalanced on a daily basis in order to reduce potential replication errors, the transaction costs effect cannot be neglected. Therefore, for each portfolio shift, 10 basis points round-trip transaction costs are taken into account (Dichtl & Drobetz, 2010; Herold et al., 2007; Hocquard et al., 2012). Additionally, the determination of the initial position does not evolve any transaction costs (Benninga, 1990, p. 22). Furthermore, the synthetic put and the protective put portfolio insurance strategy are implemented with the modified volatility estimator suggested by Boyle and Vorst (1992)[22]. Besides, in order to maintain a certain protection level, the strike price remains constant during the investment horizon. Following Figlewski et al. (1993, p. 48), the cost of buying the first put for the protective put portfolio insurance strategy is financed by borrowing at the risk-free rate. Thereafter, it is assumed that the expiring put produces a cash inflow equal to the amount by which it was in the money, if any. Then, the next put is either financed by the cash inflow of the expiring put or the reminants are borrowed at the risk-free rate. Any cash left over is invested in the risk-free asset. In order to avoid a high portfolio turnover which is triggered by trendless markets, portfolio shifts are only executed when the market moves by more than 2% (Dichtl & Drobetz, 2010; Do & Faff, 2004). Finally, the corresponding portfolio prospect values of all 100.000 simulation runs are ranked from worst to best, for computing the CPT values of each strategy.

[22] Since the assumptions are based on a Geometric Brownian motion that generates log normally distributed stock prices, the Monte Carlo simulations use the sample volatility of the generated stock prices. Usually, traders assume that the lognormal distribution understates the probability of extreme market movements, using the implied volatility instead. For the discussions on implied volatilities, please refer to Hull (2008, pp. 375 - 389). However, Dichtl and Drobetz (2010) find that volatility misestimation does not have a large impact on the CPT value of the synthetic put portfolio insurance strategy.

However, when analyzing the risk of portfolio insurance strategies which are skewed towards positive returns, the standard deviation is not an appropriate risk measure since it assumes symmetry and penalizes upside deviations from the mean as much as downside deviations. In contrast, investors tend to perceive only negative deviations as risk whereas positive deviations are regarded as chances. Lower partial moments (LPM) capture this notion of risk and are defined as (Poddig et al., 2000, p. 136)

Equation 17: Lower partial moments

$$LPM_m = \sum_{i=1}^{n'} \frac{1}{n} (\pi - r_i)^m$$

where m denotes the moments, π the threshold return, r_i the portfolio return below the threshold and n´ the number of observations below the desired threshold. Basically, the moments can be set at any value, but its choice has a strong economic meaning. LPM_0 measures the shortfall probability but contains no information on the amount of loss in case of missing the threshold return. Therefore, LPM_1 captures the mean deviations below the threshold return (expected shortfall), LPM_2 indicates the squared deviations below the threshold return (shortfall variance)[23] and $\sqrt{LPM_2}$ indicates the shortfall deviation. Since a CPT investor evaluates gains and losses in respect to the reference point of his initial wealth, the threshold rate is fixed at 0%, meaning that each negative return will enter the LPM calculations.

Consequently, the sharpe ratio is inadequately as well since it depends on the standard deviation and therefore suffers from the same shortcomings. Instead, the LPMs of the first and second order can be applied for evaluating the risk-adjusted performance of the portfolio insurance strategy. Hence, the return to shortfall (RTS) as a risk-reward ratio is calculated as (Dichtl, 2001, p. 321)

[23] In the case of $\pi = \mu$, the LPM_2 is equivalent to the semi variance suggested by Markowitz (1959) (Poddig et al., 2000, p. 136). However, the LPM measures allow to choose an arbitrary value for the threshold return which is more convenient with behavioral finance since investors separate between gains and losses in respect to the reference point of zero.

Equation 18: Return to shortfall

$$RTS_m = \frac{\bar{r}_i - \pi}{\sqrt[m]{LPM^m}}$$

where $\bar{r}_i$ denotes the average portfolio return. Consequently, the RTS_1 measures the excess return over the expected shortfall whereas the RTS_2 indicates the excess return over the shortfall deviation.

Moreover, the omega ratio, suggested by Keating and Shadwick (2002) incorporates all higher moments of the return distribution, also skewness and kurtosis. Since risk-averse investors usually prefer investment strategies that are positively skewed (positive skewness) and dislike the probability of less likely but extreme events (high kurtosis), the impact of these higher moments should not be neglected. Consequently, the omega ratio takes the whole return distribution into account and incorporates the impact of gains as well as the effects of losses, relative to the investor´s threshold return π. The omega ratio can be calculated as (Kaplan & Knowles, 2004)

Equation 19: Omega ratio

$$\Omega_\tau = \frac{\bar{r}_i - \pi}{LPM_1} + 1$$

Although the unbroken popularity of portfolio insurance strategies might not be explained by their risk-reward potential since taking over systematic risk is rewarded with an equity premium, the simulation analysis also accounts for the risk and return measures presented in this section. However, since the optimality of a portfolio insurance strategy depends on the investor´s utility function (Benninga & Blume, 1985), the main focus is on CPT values.

4.2 Base case simulation results

This section presents the base case simulation results. In the base case scenario, all portfolio insurance strategies are implemented with a protection level of 100% since CPT investors consider losses more than twice as important as gains. Furthermore, the CPPI strategy is employed with a multiplier of 2.5 (Dierkes et al., 2010) which means that the risky asset can lose at most 40% without violating the floor. In all investment markets, the annual risk-free rate is fixed at 3.5%[24] and the risk-free asset is compounded on a daily basis.

Table 2: Base case Monte Carlo simulation results MSCI Europe

	Portfolio Synthetic Put	Portfolio Protective Put	Portfolio CPPI	Portfolio Stop Loss	Portfolio Pure Stocks	Portfolio Pure Cash	Portfolio 50:50 Buy & Hold
Mean p.a.	6,27%	15,72%	4,32%	6,84%	12,24%	3,56%	7,90%
Volatility p.a.	10,26%	18,03%	2,18%	16,37%	22,00%	-	11,00%
LPM0	13,80%	18,52%	0,00%	72,46%	31,03%	-	24,64%
LPM1	0,09%	0,12%	0,00%	0,51%	3,50%	-	1,26%
√LPM2	0,35%	0,40%	0,00%	0,78%	7,87%	-	3,19%
RTS1	73,0569	126,3150	-	13,5085	3,4968	-	6,2918
RTS2	18,0231	39,0704	-	8,7253	1,2490	-	2,2908
Omega	74,0569	127,3150	-	14,5085	4,4968	-	7,2918
CPT value	4,8996**	9,7622**	3,9207**	5,2663**	1,9047	3,0582	2,5872

* The test statistic is significant at the 5% level

** The test statistic is significant at the 1% level

As expected, the stock market investment exhibits the highest annual mean return (apart from the protective put strategy) due to the risk premium effect (12.24%). Although the portfolio insurance strategies provide a reduced return potential, their annual standard deviation is significantly lower in regards to that of the stock market investment. However, since the standard deviation is not an appropriate risk measure, the LPMs provide more liable insight into the risk involved. The LPM_0 indicates that the probability of negative returns is relatively high for the benchmark portfolios (31.03% for the stock investment and 24.64% for the buy and hold investment, respectively), but significantly higher for the stop loss strategy (72.46%). But this mitigates when the LPM_1 is taken into consideration, since the expected shortfall is relatively small (0.51%). A possible explanation for this finding is that the stop loss strategy fails to compensate a sudden

[24] Initially, it was intended to calculate the risk-free rate from historical data. However, the corresponding risk-free rate depends as well on the respective market capitalization per country of the MSCI indices. Unfortunately, this information was not available.

loss in stock prices at an early stage of the investment horizon, ending up more often slightly below the pre-specified floor as time elapses. Nevertheless, all portfolio insurance strategies dominate the benchmark strategies in regard to their LPM_1 and $\sqrt{LPM_2}$, indicating significantly lower downside risk. Moreover, the CPPI strategy even shows no downside risk at all but also yields the lowest annual mean return apart from the cash investment. Hence, the portfolio insurance strategies significantly dominate the benchmark strategies regarding their risk-adjusted returns whereas the RTS_1, RTS_2 and omega ratio show the same rankings: the protective put provides the highest risk-reward ratios, followed by the synthetic put, the stop loss strategy and the benchmark strategies[25].

When the analysis is based on CPT values, all portfolio insurance strategies dominate the respective benchmark strategies as well. While the stock market investment provides the highest annual mean return, it is the least attractive strategy regarding its CPT value (1.9047). This finding can be explained by both, loss aversion and the probability weighting scheme. Since the passive stock market strategy contains the highest downside risk (LPM_1 3.50% and $\sqrt{LPM_2}$ 7.87%), the negative CPT values during one year investment horizon cannot be offset by the positive risk-premium effect. Also, extreme adverse states receive higher probability weights which further contribute to the relatively poor performance of the stock investment regarding its CPT value. More interestingly, the ranking of the CPT values is different from that of the risk-reward ratios. Although the protective put strategy is still the preferable investment strategy, the stop loss strategy is now the second attractive one, followed by the synthetic put strategy, the CPPI strategy and the benchmark strategies. Hence, the CPPI investment strategy seems to be the least attractive portfolio insurance strategy for a CPT investor, despite of not having any downside risk at all. In fact, with an annual mean return of 4.32%, the CPPI strategy exhibits only a slightly better annual mean return than the cash investment (3.56%). However, the different ranking of the risk-reward ratios and the CPT values can once more be explained by the probability weighting scheme: The risk-reward measures only capture the probability of positive and negative outcomes whereas the CPT probability weighting function puts extra weights on the tails of the return distribution, thereby overestimating low probability events. Regarding the poor CPT value of the passive stock market investment (1.9047) compared to that of the buy and hold strategy

[25] Since the CPPI portfolio insurance strategy and the cash investment exhibit no downside risk, the risk-reward ratios are not defined.

(2.5872), it seems that several extremely adverse states occurred. Among the benchmark strategies, the money market investment yields the highest CPT value (3.0582) since it earns an annual return without any loss potential. However, although the cash investment seems to be an attractive investment strategy for a CPT investor, it is dominated by all four portfolio insurance strategies regarding its CPT value. A paired t-test[26] reveals that the CPT values of the portfolio insurance strategies significantly differ from the CPT value of the cash investment (which is the benchmark strategy yielding the highest CPT value). All differences are statistically significant at the 1% level. Consequently, it seems that portfolio insurance strategies provide an attractive investment strategy for an investor with CPT preferences, whereas the protective put strategy seems to be the most attractive one, followed by the stop loss strategy, the synthetic put strategy and the CPPI strategy.

Table 3: Base case Monte Carlo simulation results MSCI USA

	Portfolio Synthetic Put	Portfolio Protective Put	Portfolio CPPI	Portfolio Stop Loss	Portfolio Pure Stocks	Portfolio Pure Cash	Portfolio 50:50 Buy & Hold
Panel A: Protection level = 100%							
Mean p.a.	6,53%	15,21%	4,33%	7,13%	12,33%	3,56%	7,95%
Volatility p.a.	9,90%	16,67%	1,96%	15,65%	20,09%	-	10,04%
LPM0	14,39%	17,17%	0,00%	69,55%	28,59%	-	21,97%
LPM1	0,11%	0,11%	0,00%	0,44%	2,90%	-	1,00%
√LPM2	0,43%	0,36%	0,00%	0,70%	6,82%	-	2,70%
RTS1	59,4320	142,9811	-	16,0608	4,2556	-	7,9443
RTS2	15,1160	42,5584	-	10,1695	1,5132	-	2,7564
Omega	60,4320	143,9811	-	17,0608	5,2556	-	8,9443
CPT value	3,8716**	5,3618**	4,7190**	3,3274**	2,5635	3,0582	2,9330

* The test statistic is significant at the 5% level

** The test statistic is significant at the 1% level

Basically, the Monte Carlo simulation results of the MSCI USA index lead to the same conclusions. Again, the stock market investment yields the highest annual mean return (with the exception of the protective put strategy), whereas the portfolio insurance strategies provide a lower return potential due to the risk premium effect. Also, the LPM_0 indicates a high probability of negative returns for the benchmark investments (28.59% for the passive stock investment and 21.97% for the buy and hold strategy) and the stop loss strategy (69.55%), presumably due to the same reasons as explained before since

[26] Although there exist more powerful hypothesis tests which take the whole distribution into account (Linton et al., 2005), a paired t-test is frequently used to test the significance in differences of portfolio insurance strategies (Annaert et al., 2009; Dichtl & Drobetz, 2010).

the expected shortfall of the stop loss strategy is negligibly small (LPM_1 0.44%). Besides, the benchmark strategies exhibit significantly higher shortfall deviations than the portfolio insurance strategies ($\sqrt{LPM_2}$ 2.90% for the stock strategy and 1.00% for the buy and hold strategy, respectively) which are once more reflected in the risk-reward ratios. Surprisingly, the ranking of the risk-reward ratios is equal to that of the CPT values (apart from the CPPI strategy and the cash investment since their risk-reward ratios are not defined). Hence it seems that less extreme negative events occurred whose impacts on CPT values are not that severe. This assumption is even more likely since the difference between the CPT value of the stock investment (2.5635) and the buy and hold investment (2.9330) is not that pronounced as in the MSCI Europe simulation (Table 1). However, the portfolio insurance strategies again dominate the corresponding benchmark strategies regarding their CPT values. As a paired t-test reveals, the CPT values of the portfolio insurance strategies significantly differ from that of the cash investment (which is again the benchmark with the highest CPT value). All differences are statistically significant at the 1% level.

Table 4: Base Case Monte Carlo simulation results MSCI World

	Portfolio Synthetic Put	Portfolio Protective Put	Portfolio CPPI	Portfolio Stop Loss	Portfolio Pure Stocks	Portfolio Pure Cash	Portfolio 50:50 Buy & Hold
Panel A: Protection level = 100%							
Mean p.a.	6,22%	13,49%	4,20%	6,74%	10,91%	3,56%	7,24%
Volatility p.a.	8,98%	14,63%	1,68%	14,03%	17,73%	-	8,86%
LPM0	16,18%	16,97%	0,00%	67,43%	28,38%	-	21,10%
LPM1	0,16%	0,10%	0,00%	0,38%	2,59%	-	0,86%
√LPM2	0,58%	0,32%	0,00%	0,62%	6,14%	-	2,37%
RTS1	38,6696	140,6858	-	17,5941	4,2070	-	8,4328
RTS2	10,6781	41,7562	-	10,9628	1,7771	-	3,0509
Omega	39,6696	141,6858	-	18,5941	5,2070	-	9,4328
CPT value	4,311**	8,3974**	3,8472**	4,9576**	2,1776	3,0582	2,7377

* The test statistic is significant at the 5% level

** The test statistic is significant at the 1% level

Once more, the Monte Carlo simulation of the MSCI World index leads to the same results. Apart from the protective put strategy, the stock market investment and the buy and hold investment dominate the portfolio insurance strategies in regard to their annual mean returns (10.91% and 7.24%, respectively) but compare unfavorably regarding their risk measures. Besides, the risk-reward ratios and CPT values rank the investment strategies differently, thereby indicating the occurrence of extremely adverse events. However, since the difference between the CPT value of the passive stock investment

(2.1776) and the buy and hold investment (2.7377) is not that large in magnitude, it seems that only few extremely adverse states occurred. Again, all portfolio insurance strategies significantly dominate the respective benchmark portfolios regarding their CPT values at the 1% level. For an investor with CPT preferences, the protective put strategy is once more the most attractive portfolio insurance strategy, followed by the CPPI strategy, the synthetic put strategy and the stop loss strategy.

When comparing the results of all three Monte Carlo base case simulations, the following patterns are observable: Regarding the fact that the Monte Carlo simulations of the MSCI Europe and MSCI USA indices yield almost the same stock markets returns (12.24% and 12.33%) but different volatilities (22% and 20.09%), it seems that the higher the volatility, the better the CPT values of the portfolio insurance strategies (Table 2 and Table 3, respectively). This observation can be explained by the high degree of loss aversion which is also consistent with the findings of Hwang and Satchell (2010, p. 2437) that investors are more risk averse than usually assumed. Furthermore, in the absence of extremely adverse states, it seems that the ranking of the risk-reward ratios is equal to that of the CPT values but it differs in the case of extreme outcomes. One possible explanation of this finding is the probability weighting scheme: The risk-reward ratios only capture the probability of positive and negative outcomes whereas the CPT probability weighting function puts extra weights on the tails of the return distribution, thereby overestimating low probability events. However, the main result is not affected by differences in volatilities and rankings of the investment strategies. All three stock market simulations provide qualitatively similar results as the portfolio insurance strategies dominate – without any exception - the benchmark strategies regarding their CPT values. This is also consistent with the findings of Dichtl and Drobetz (2010). Nevertheless, in order to gain more detailed insight, an extensive sensitivity analysis is conducted.

4.3 Sensitivity analysis

When changing the input parameters for conducting the sensitivity analysis, the same 100.000 price series of each particular MSCI index is used. Although this might lead to some bias because the same sampling error enters into the results, using the same price series allows for a better comparison of the behavior of the investment strategies (Figlewski et al., 1993, p. 50). Nevertheless, since the accuracy of the simulation result highly depends on the number of trials, the standard errors of each Monte Carlo simulation are computed as (Hull, 2008, p. 414)

Equation 20: Standard error of Monte Carlo simulation

$$\mathrm{SE} = \frac{\sigma}{\sqrt{\mathrm{M}}}$$

whereas M denotes the number of trials. Given a sampling error of 0.06% for the Monte Carlo simulations MSCI Europe index, 0.05% for the MSCI USA index and 0.04% for the MSCI World index, respectively, the simulation results of 100.000 simulation runs provide an adequate degree of accuracy[27], indicating qualitatively good simulation results.

4.3.1 Varying the protection level

Since CPT investors are very sensitive to the possibility of losses, the impact of changing the protection level cannot be neglected. However, the higher the protection level, the lower the respective return potential. It is unclear if a higher return potential can compensate for the reduced protection level regarding CPT values. Therefore, the Monte Carlo simulations are repeated with a 90% protection level.

[27] The accuracy of the simulation results was already confirmed by the results shown in Table 1 since the theoretical values for the annual mean return and volatility are very close to the simulated ones.

Table 5: Monte Carlo simulation results MSCI Europe: Varying the protection level

	Portfolio Synthetic Put	Portfolio Protective Put	Portfolio CPPI	Portfolio Stop Loss	Portfolio Pure Stocks	Portfolio Pure Cash	Portfolio 50:50 Buy & Hold
Panel A: Protection level = 100%							
Mean p.a.	6,27%	15,72%	4,32%	6,84%	12,24%	3,56%	7,90%
Volatility p.a.	10,26%	18,03%	2,18%	16,37%	22,00%	-	11,00%
LPM0	13,80%	18,52%	0,00%	72,46%	31,03%	-	24,64%
LPM1	0,09%	0,12%	0,00%	0,51%	3,50%	-	1,26%
√LPM2	0,35%	0,40%	0,00%	0,78%	7,87%	-	3,19%
RTS1	73,0569	126,3150	-	13,5085	3,4968	-	6,2918
RTS2	18,0231	39,0704	-	8,7253	1,2490	-	2,2908
Omega	74,0569	127,3150	-	14,5085	4,4968	-	7,2918
CPT value	4,8996**	9,7622**	3,9207**	5,2663**	1,9047	3,0582	2,5872
Panel B: Protection level = 90%							
Mean p.a.	9,97%	13,48%	6,46%	10,82%	12,24%	3,56%	7,90%
Volatility p.a.	18,16%	20,26%	8,35%	21,74%	22,00%	-	11,00%
LPM0	37,48%	31,03%	21,58%	40,46%	31,03%	-	24,64%
LPM1	2,52%	2,26%	0,50%	3,87%	3,50%	-	1,26%
√LPM2	4,55%	4,49%	1,31%	6,33%	7,87%	-	3,19%
RTS1	3,9586	5,9548	13,0465	2,7959	3,4968	-	6,2918
RTS2	2,1937	3,0002	4,9513	1,7107	1,2490	-	2,2908
Omega	4,9586	6,9548	14,0465	3,7959	4,4968	-	7,2918
CPT value	3,4273**	5,3613**	3,5611**	2,9413**	1,9047	3,0582	2,5872

* The test statistic is significant at the 5% level

** The test statistic is significant at the 1% level

As expected, the annual mean returns as well as the downside risk measures increase when the floor is reduced. As the LPM_0 indicates, nearly all portfolio insurance strategies exhibit significantly higher shortfall probabilities: the synthetic put strategy (13.80% vs. 37.48%), the protective put strategy (18.52% vs. 31.03%) and the CPPI strategy (0% vs. 21.58%) which does not even relax by taking the LMP_1 into account. Moreover, the shortfall deviations of the synthetic put strategy ($\sqrt{LPM_2}$ 4.55%) and the protective put strategy ($\sqrt{LPM_2}$ 4.49%) are significantly higher than that of the buy and hold strategy ($\sqrt{LPM_2}$ 3.19%), whereas the stop loss portfolio strategy even exhibits a shortfall deviation comparable to that of the passive stock investment ($\sqrt{LPM_2}$ 6.33% vs. 7.87%). The CPPI strategy provides the only exception regarding its downside risk measures, still containing the lowest shortfall deviation ($\sqrt{LPM_2}$ 1.31%). Consequently, the risk-reward ratios reflect the poor performance of the portfolio insurance strategies at a lower protection level. This is particularly pronounced for the synthetic put strategy and stop loss strategy since they are dominated by the buy and hold strategy whereas the stop loss strategy is even partly dominated by the stock investment. However, according to risk-reward ratios no clear dominance can be found: some portfolio insurance strategies dominate the benchmark strategies regarding their risk and return measures but some are dominated.

Again, a paired t-test reveals that the differences in CPT values between the money market investment (being the best performing benchmark strategy in terms of its CPT value) and the portfolio insurance strategies are highly significant at the 1% level. In contrast to the findings of Dichtl and Drobetz (2010) that all portfolio insurance strategies implemented with a 90% protection level are dominated by the cash investment regarding their CPT values, only the stop loss portfolio insurance strategy exhibits a significantly lower CPT value than the money market investment (2.9413 vs. 3.0582). As the LPM_0 indicates, the probability of earning a loss is significantly lower at the 90% protection level (40.46% vs. 72.46%) but the corresponding loss is large in magnitude ($\sqrt{LPM_2}$ 6.33% vs. 0.78%). Although the stop loss strategy yields a relatively high annual mean return (10.82%), CPT investors care more than twice as much about potential losses than about potential gains. Therefore they prefer the cash investment without any loss potential over the stop loss portfolio insurance strategy implemented at a lower protection level. For the protective put strategy, on the other hand, the probability of earning a loss is significantly higher when implemented with a 90% protection level (LPM_0 31.03% vs. 18.52%), but it seems the high shortfall deviation ($\sqrt{LPM_2}$ 4.99%) results from some extremely adverse events whose negative effects could be offset by the positive prospect values of many good states, as the high annual mean return indicates (13.48%). Additionally, the different ranking of the risk-reward ratios and the CPT values indicate probability distortions, thereby supporting this assumption. However, apart from the stop loss portfolio insurance strategy, the portfolio insurance strategies again significantly dominate the corresponding benchmark strategies regarding their CPT values.

Table 6: Monte Carlo simulation results MSCI USA: Varying the protection level

	Portfolio Synthetic Put	Portfolio Protective Put	Portfolio CPPI	Portfolio Stop Loss	Portfolio Pure Stocks	Portfolio Pure Cash	Portfolio 50:50 Buy & Hold
Panel A: Protection level = 100%							
Mean p.a.	6,53%	15,21%	4,33%	7,13%	12,33%	3,56%	7,95%
Volatility p.a.	9,90%	16,67%	1,96%	15,65%	20,09%	-	10,04%
LPM0	14,39%	17,17%	0,00%	69,55%	28,59%	-	21,97%
LPM1	0,11%	0,11%	0,00%	0,44%	2,90%	-	1,00%
√LPM2	0,43%	0,36%	0,00%	0,70%	6,82%	-	2,70%
RTS1	59,4320	142,9811	-	16,0608	4,2556	-	7,9443
RTS2	15,1160	42,5584	-	10,1695	1,5132	-	2,7564
Omega	60,4320	143,9811	-	17,0608	5,2556	-	8,9443
CPT value	3,8716**	5,3618**	4,7190**	3,3274**	2,5635	3,0582	2,9330
Panel B: Protection level = 90%							
Mean p.a.	10,32%	13,23%	6,52%	11,16%	12,33%	3,56%	7,95%
Volatility p.a.	17,06%	18,75%	7,54%	20,12%	20,09%	-	10,04%
LPM0	33,86%	28,59%	18,05%	36,08%	28,59%	-	21,97%
LPM1	2,18%	2,00%	0,37%	3,33%	2,90%	-	1,00%
√LPM2	4,21%	4,18%	1,09%	5,83%	6,82%	-	2,70%
RTS1	4,7302	6,6163	17,3820	3,3520	4,2556	-	7,9443
RTS2	2,4489	3,1639	5,9802	1,9160	1,5132	-	2,7564
Omega	5,7302	7,6163	18,3820	4,3520	5,2556	-	8,9443
CPT value	3,6587**	5,3032**	3,6607**	3,2812**	2,5635	3,0582	2,9330

* The test statistic is significant at the 5% level

** The test statistic is significant at the 1% level

Generally, the Monte Carlo simulation results of the MSCI USA index lead to the same conclusions. The annual mean returns as well as the downside risk measures increase when the floor is reduced. Once more, the stop loss portfolio insurance strategy is the worst performing investment strategy regarding its downside risk. The high shortfall probability (LPM_0 36.08%) results in a higher expected shortfall than that of the stock investment (LPM_1 3.33% vs. 2.90%). Although the shortfall deviation of the stop loss strategy compares better to that of the passive stock market investment ($\sqrt{LPM_2}$ 5.83% vs. 6.82%), the stop loss strategy exhibits a significantly higher shortfall deviation than the buy and hold investment ($\sqrt{LPM_2}$ 5.83% vs. 2.70%). Besides, both, the synthetic put and the stop loss strategy are dominated by the buy and hold strategy regarding their risk-reward ratios, whereas the stop loss strategy is even dominated by the stock investment. The CPPI strategy provides the only exception regarding its risk-reward ratios, thereby dominating the passive stock investment and the buy and hold investment. However, since the CPPI strategy outperforms the benchmark strategies regarding its risk-reward ratios, no clear dominance can be found.

But these findings reverse when the analysis is based on CPT values. As a paired t-test reveals, all portfolio insurance strategies (even the stop loss strategy) significantly dominate the cash market investment at a 1% level (which is once more the benchmark strategy yielding the highest CPT value). Presumably, the relatively high shortfall deviation of the stop loss portfolio insurance strategy ($\sqrt{LPM_2}$ 5.83%) results from some less severe adverse events whose negative effects could be compensated by the positive prospect values of many other good states, as the relatively high annual mean return indicates (11.16%). This assumption seems even more likely since the ranking of the risk-reward ratios and that of the CPT values is exactly the same, thereby indicating no probability distortions and the occurrence of less severe events.

Table 7: Monte Carlo simulation results MSCI World: Varying the protection level

	Portfolio Synthetic Put	Portfolio Protective Put	Portfolio CPPI	Portfolio Stop Loss	Portfolio Pure Stocks	Portfolio Pure Cash	Portfolio 50:50 Buy & Hold
Panel A: Protection level = 100%							
Mean p.a.	6,22%	13,49%	4,20%	6,74%	10,91%	3,56%	7,24%
Volatility p.a.	8,98%	14,63%	1,68%	14,03%	17,73%	-	8,86%
LPM0	16,18%	16,97%	0,00%	67,43%	28,38%	-	21,10%
LPM1	0,16%	0,10%	0,00%	0,38%	2,59%	-	0,86%
√LPM2	0,58%	0,32%	0,00%	0,62%	6,14%	-	2,37%
RTS1	38,6696	140,6858	-	17,5941	4,2070	-	8,4328
RTS2	10,6781	41,7562	-	10,9628	1,7771	-	3,0509
Omega	39,6696	141,6858	-	18,5941	5,2070	-	9,4328
CPT value	4,311**	8,3974**	3,8472**	4,9576**	2,1776	3,0582	2,7377
Panel B: Protection level = 90%							
Mean p.a.	9,46%	11,61%	6,02%	10,13%	10,91%	3,56%	7,24%
Volatility p.a.	15,36%	16,65%	6,43%	17,77%	17,73%	-	8,86%
LPM0	32,27%	28,38%	16,10%	33,70%	28,38%	-	21,10%
LPM1	2,02%	1,90%	0,30%	2,94%	2,59%	-	0,86%
√LPM2	4,06%	4,03%	0,95%	5,42%	6,14%	-	2,37%
RTS1	4,6928	6,1143	19,8576	3,4411	4,2070	-	8,4328
RTS2	2,3268	2,8822	6,3662	1,8693	1,7771	-	3,0509
Omega	5,6928	7,1143	20,8576	4,4411	5,2070	-	9,4328
CPT value	3,1134**	4,4291**	3,3679**	2,8588**	2,1776	3,0582	2,7377

* The test statistic is significant at the 5% level

** The test statistic is significant at the 1% level

The Monte Carlo simulation of the MSCI World, however, depicts the same picture as the MSCI Europe simulations at a 90% protection level (Table 5). Although all portfolio insurance strategies yield higher annual mean returns, they exhibit significantly higher downside risk as well. Again, this is particularly pronounced for the stop loss strategy which shows only a slightly lower shortfall deviation than the stock market investment ($\sqrt{LPM_2}$ 5.42% vs. 6.14%). Besides, all portfolio insurance strategies (with the exception of the protective put strategy) are once more dominated by the buy and hold investment in terms of their risk-reward ratios, whereas the stop loss strategy is even partly dominated by the stock investment. A paired t-test reveals that the differences in CPT values between the money market investment (being the best performing benchmark strategy in terms of its CPT value) and the portfolio insurance strategies are highly significant at the 1% level. Once again, the stop loss portfolio insurance strategy exhibits a significantly lower CPT value than the cash investment (2.8588 vs. 3.0582) and only a slightly better CPT value than the buy and hold strategy (2.8588 vs. 2.7377). Regarding the fact that the stop loss portfolio investment strategy yields almost the same annual mean return as the stock investment (10.13% vs. 10.91%) and only a slightly lower shortfall deviation ($\sqrt{LPM_2}$ 5.42% vs. 6.14%), it seems that the stop loss strategy almost behaved like the stock investment. Presumably, some extremely adverse events occurred whose negative prospect values could not be offset by the positive prospect values of good states. This assumption is once more supported by the different ranking of the risk-reward ratios and CPT values, indicating probability distortions.

Generally, despite of a higher return potential, implementing the portfolio insurance strategies with a 90% protection level leads to an overall reduction in CPT values, indicating their inferiority for an investor with CPT preferences. Hence, it seems that an investment strategy with a 100% protection level is more attractive for a CPT investor due to the high degree of loss aversion. Additionally, in the Monte Carlo simulations of the MSCI Europe and MSCI World indices, the impact of a lower protection level is particularly pronounced for the protective put strategy and the stop loss strategy since their CPT values nearly halved compared to those implemented with a full capital guarantee. Moreover, the stop loss strategy even exhibits lower CPT values than the money market investment (Table 5 and Table 7, respectively). A possible explanation for this finding is that any losses that cannot be recovered within one year investment horizon are heavily weighted, resulting in low CPT values. Notably, in the Monte Carlo simulations of the MSCI USA index, a 90% protection level leads to insignificantly lower CPT values but the dominance of all portfolio insurance strategies (Table 6). Presumably, less extreme negative events occurred whose negative impact on CPT values is not that severe. This assumption is even more likely since the volatility of the stock market returns is relatively low compared to that of the MSCI Europe index. Also, the difference in the CPT values of the stock investment (2.5635) and the buy and hold investment (2.9330) is not that pronounced, indicating the occurrence of less extreme adverse events. However, as observable in all Monte Carlo simulations, implementing the portfolio insurance strategies with a higher protection level seems more beneficial for an investor with CPT preferences[28].

4.3.2 Varying the risk-free rate

Although the recent past was characterized by low interest rates, future interest rates might be at a higher level which could easily lead to different conclusions. Therefore, as another battery of robustness tests, the Monte Carlo simulations are repeated with a risk-free rate of 5.5%. In a first step, the portfolio insurance strategies are implemented with a 100% protection level and in a second step, with a 90% protection level.

Table 8: Monte Carlo simulation results MSCI Europe: Varying the risk-free rate,100% protection level

	Portfolio Synthetic Put	Portfolio Protective Put	Portfolio CPPI	Portfolio Stop Loss	Portfolio Pure Stocks	Portfolio Pure Cash	Portfolio 50:50 Buy & Hold
Panel A: Risk-free rate = 3,5%							
Mean p.a.	6,27%	15,72%	4,32%	6,84%	12,24%	3,56%	7,90%
Volatility p.a.	10,26%	18,03%	2,18%	16,37%	22,00%	-	11,00%
LPM0	13,80%	18,52%	0,00%	72,46%	31,03%	-	24,64%
LPM1	0,09%	0,12%	0,00%	0,51%	3,50%	-	1,26%
√LPM2	0,35%	0,40%	0,00%	0,78%	7,87%	-	3,19%
RTS1	73,0569	126,3150	-	13,5085	3,4968	-	6,2918
RTS2	18,0231	39,0704	-	8,7253	1,2490	-	2,2908
Omega	74,0569	127,3150	-	14,5085	4,4968	-	7,2918
CPT value	4,8996**	9,7622**	3,9207**	5,2663**	1,9047	3,0582	2,5872
Panel B: Risk-free rate = 5,5%							
Mean p.a.	8,30%	15,73%	6,52%	8,89%	12,24%	5,65%	8,95%
Volatility p.a.	12,07%	18,03%	3,28%	17,63%	22,00%	-	11,00%
LPM0	12,49%	18,25%	0,00%	61,05%	31,03%	-	21,20%
LPM1	0,09%	0,13%	0,00%	0,42%	3,50%	-	1,02%
√LPM2	0,38%	0,40%	0,00%	0,70%	7,87%	-	2,79%
RTS1	90,7595	125,5672	-	21,3114	3,4968	-	8,8032
RTS2	22,0351	38,9571	-	12,6275	1,2490	-	2,9916
Omega	91,7595	126,5672	-	22,3114	4,4968	-	9,8032
CPT value	6,0221**	9,7627**	5,6475**	6,3676**	1,9047	4,5923	3,4696

* The test statistic is significant at the 5% level
** The test statistic is significant at the 1% level

As expected, the annual mean returns and the CPT values of the portfolio insurance strategies increase with a higher risk-free rate. Unsurprisingly, the results of the protective put portfolio insurance strategy remain unchanged since it is assumed that the

[28] This finding is consistent with Dichtl and Drobetz (2010).

expiring put is either financed by borrowing at the risk-free rate or any cash left over is invested at the same risk-free rate. Consequently, the higher deposit risk-free rate is offset by that of the loans. Additionally, although the cash investment becomes more attractive for a CPT investor the higher the risk-free rate (4.5923 vs. 3.0582), the dominance of the portfolio insurance strategies against the money market investment remains unchanged. Again, a paired t-test is conducted in order to validate that the CPT values of the portfolio insurance strategies significantly differ from that of the cash investment. All differences are statistically significant at the 1% level. Furthermore, the ranking of the CPT values does not change by varying the risk-free rate: The protective put strategy (9.7627) followed by the stop loss strategy (6.3676), the synthetic put strategy (6.0221) and the CPPI strategy (5.6475) are the most attractive investment strategies for an investor with CPT preferences.

Table 9: Monte Carlo simulation results MSCI USA: Varying the risk-free rate, 100% protection level

	Portfolio Synthetic Put	Portfolio Protective Put	Portfolio CPPI	Portfolio Stop Loss	Portfolio Pure Stocks	Portfolio Pure Cash	Portfolio 50:50 Buy & Hold
Panel A: Risk-free rate = 3,5%							
Mean p.a.	6,53%	15,21%	4,33%	7,13%	12,33%	3,56%	7,95%
Volatility p.a.	9,90%	16,67%	1,96%	15,65%	20,09%	-	10,04%
LPM0	14,39%	17,17%	0,00%	69,55%	28,59%	-	21,97%
LPM1	0,11%	0,11%	0,00%	0,44%	2,90%	-	1,00%
√LPM2	0,43%	0,36%	0,00%	0,70%	6,82%	-	2,70%
RTS1	59,4320	142,9811	-	16,0608	4,2556	-	7,9443
RTS2	15,1160	42,5584	-	10,1695	1,5132	-	2,7564
Omega	60,4320	143,9811	-	17,0608	5,2556	-	8,9443
CPT value	3,8716**	5,3618**	4,7190**	3,3274**	2,5635	3,0582	2,9330
Panel B: Risk-free rate = 5,5%							
Mean p.a.	8,54%	15,21%	6,54%	9,19%	12,33%	5,65%	8,99%
Volatility p.a.	11,56%	16,67%	2,96%	16,72%	20,09%	-	10,04%
LPM0	13,13%	16,88%	0,00%	57,57%	28,59%	-	18,58%
LPM1	0,12%	0,11%	0,00%	0,36%	2,90%	-	0,79%
√LPM2	0,47%	0,36%	0,00%	0,63%	6,82%	-	2,33%
RTS1	72,6792	142,1402	-	25,5883	4,2556	-	11,4031
RTS2	18,2788	42,4215	-	14,6979	1,5132	-	3,6439
Omega	73,6792	143,1402	-	26,5883	5,2556	-	12,4031
CPT value	5,8954**	5,3622**	5,7297**	6,3801**	2,5635	4,5923	3,8066

* The test statistic is significant at the 5% level

** The test statistic is significant at the 1% level

Generally, varying the risk-free rate in the Monte Carlo simulations of the MSCI USA index leads to the same conclusions. All portfolio insurance strategies exhibit higher annual mean returns and CPT values, respectively. Again, the values for the protective put strategy remain unchanged since the put premium is refinanced at the same risk-free rate as the deposits are compounded. More interestingly, the ranking of the CPT values differs from that of a lower risk-free rate. Apparently, the stop loss portfolio insurance strategy yields higher CPT values (6.3801) than the CPPI strategy (5.7297). This finding can be explained by the fact that the stop loss portfolio insurance strategy fully invests the investor´s initial wealth in the risky asset until the portfolio value reaches or drops below the NPV of the floor, whereas the CPPI strategy only partially invests the investor´s wealth in the risky asset, thereby losing some upward potential in very good states. This is consistent with the findings of Cesari and Cremonini (2003, p. 997) that the CPPI strategy yields a good performance in bear and sideway markets but not in bull markets. However, all portfolio insurance strategies significantly dominate the cash market investment regarding their CPT values at the 1% level, indicating that they are more attractive for an investor with CPT preferences.

Table 10: Monte Carlo simulation results MSCI World: Varying the risk-free rate,100% protection level

	Portfolio Synthetic Put	Portfolio Protective Put	Portfolio CPPI	Portfolio Stop Loss	Portfolio Pure Stocks	Portfolio Pure Cash	Portfolio 50:50 Buy & Hold
Panel A: Risk-free rate = 3,5%							
Mean p.a.	6,22%	13,49%	4,20%	6,74%	10,91%	3,56%	7,24%
Volatility p.a.	8,98%	14,63%	1,68%	14,03%	17,73%	-	8,86%
LPM0	16,18%	16,97%	0,00%	67,43%	28,38%	-	21,10%
LPM1	0,16%	0,10%	0,00%	0,38%	2,59%	-	0,86%
√LPM2	0,58%	0,32%	0,00%	0,62%	6,14%	-	2,37%
RTS1	38,6696	140,6858	-	17,5941	4,2070	-	8,4328
RTS2	10,6781	41,7562	-	10,9628	1,7771	-	3,0509
Omega	39,6696	141,6858	-	18,5941	5,2070	-	9,4328
CPT value	4,311**	8,3974**	3,8472**	4,9576**	2,1776	3,0582	2,7377
Panel B: Risk-free rate = 5,5%							
Mean p.a.	8,06%	13,49%	6,35%	8,58%	10,91%	5,65%	8,28%
Volatility p.a.	10,45%	14,62%	2,53%	14,86%	17,73%	-	8,86%
LPM0	14,90%	16,67%	0,00%	54,92%	28,38%	-	17,42%
LPM1	0,18%	0,10%	0,00%	0,31%	2,59%	-	0,66%
√LPM2	0,64%	0,32%	0,00%	0,55%	6,14%	-	2,01%
RTS1	45,9225	140,0645	-	27,9598	4,2070	-	12,6095
RTS2	12,5637	41,6731	-	15,6940	1,7771	-	4,1164
Omega	46,9225	141,0645	-	28,9598	5,2070	-	13,6095
CPT value	5,275**	8,3986**	5,5055**	5,9011**	2,1776	4,5923	3,6161

* The test statistic is significant at the 5% level

** The test statistic is significant at the 1% level

Basically, the Monte Carlo simulations of the MSCI World index lead to the same conclusions. All portfolio insurance strategies yield higher annual mean returns as well as CPT values at a higher risk-free rate, whereas the protective put portfolio insurance strategy exhibits the same results due to equal risk-free rates for deposits and loans. Moreover, the ranking of the CPT values does not differ from that with a lower risk-free rate. As a paired t-test reveals, all portfolio insurance strategies significantly dominate the cash investment (being once more the best performing benchmark strategies regarding its CPT values) at the 1% level.

Overall, the Monte Carlo simulations reveal that a higher risk-free rate results in higher annual mean returns and CPT values, respectively. Since the annual stock market return remains the same but the risk-free rate increases, this observation can be explained by the lower opportunity costs of the portfolio insurance strategies. As the implicit costs of insuring the portfolio rather than earning the unprotected annual return of the stock market investment decreases (lower opportunity costs), the portfolio insurance strategies seem even more attractive for a CPT investor. However, it remains unclear if a lower protection level leads to the same conclusions. Therefore, the Monte Carlo simulations are repeated implementing a protection level of 90% and a risk-free rate of 5.5%.

Table 11: Monte Carlo simulation results MSCI Europe: Varying the risk-free rate,90% protection level

	Portfolio Synthetic Put	Portfolio Protective Put	Portfolio CPPI	Portfolio Stop Loss	Portfolio Pure Stocks	Portfolio Pure Cash	Portfolio 50:50 Buy & Hold
Panel A: Risk-free rate = 3,5%							
Mean p.a.	9,97%	13,48%	6,46%	10,82%	12,24%	3,56%	7,90%
Volatility p.a.	18,16%	20,26%	8,35%	21,74%	22,00%	-	11,00%
LPM0	37,48%	31,03%	21,58%	40,46%	31,03%	-	24,64%
LPM1	2,52%	2,26%	0,50%	3,87%	3,50%	-	1,26%
√LPM2	4,55%	4,49%	1,31%	6,33%	7,87%	-	3,19%
RTS1	3,9586	5,9548	13,0465	2,7959	3,4968	-	6,2918
RTS2	2,1937	3,0002	4,9513	1,7107	1,2490	-	2,2908
Omega	4,9586	6,9548	14,0465	3,7959	4,4968	-	7,2918
CPT value	3,4273**	5,3613**	3,5611**	2,9413**	1,9047	3,0582	2,5872
Panel B: Risk-free rate = 5,5%							
Mean p.a.	10,70%	13,48%	8,08%	11,32%	12,24%	5,65%	8,95%
Volatility p.a.	18,50%	20,26%	9,17%	21,57%	22,00%	-	11,00%
LPM0	35,89%	31,03%	16,55%	38,65%	31,03%	-	21,20%
LPM1	2,41%	2,26%	0,36%	3,63%	3,50%	-	1,02%
√LPM2	4,45%	4,49%	1,08%	6,10%	7,87%	-	2,79%
RTS1	4,4458	5,9573	22,6205	3,1170	3,4968	-	8,8032
RTS2	2,4054	3,0014	7,4522	1,8544	1,2490	-	2,9916
Omega	5,4458	6,9573	23,6205	4,1170	4,4968	-	9,8032
CPT value	3,8716**	5,3618**	4,7190**	3,3274**	1,9047	4,5923	3,4696

* The test statistic is significant at the 5% level

** The test statistic is significant at the 1% level

As expected, a higher risk-free rate does not alter the annual mean returns as much as in the Monte Carlo simulation with a 100% protection level (Table 8) since the portfolio insurance strategies behave more like the passive stock market investment when implemented with a lower protection level. The impact on CPT values, however, is more pronounced. At a lower protection level and a higher risk-free rate, the cash investment seems even more attractive for an investor with CPT preferences since it yields a CPT value of 4.5923 without having any loss potential. As a result, both, the stop loss portfolio insurance strategy (as in the case with a risk-free rate of 3.5%) and the synthetic put strategy yield lower CPT values than the cash investment (3.3274 and 3.8716 vs. 4.5923), whereas the stop loss strategy even exhibits a lower CPT value than the buy and hold investment (3.3274 vs. 3.4696). As a paired t-test reveals, all differences are statistically significant at the 1% level. Hence, it seems that the positive impact from a higher risk-free rate cannot completely compensate for the negative impact of a lower protection level. This is especially pronounced for the synthetic put portfolio insurance strategy since it is not dominated by the cash investment at the 100% protection level.

Table 12: Monte Carlo simulation results MSCI USA: Varying the risk-free rate, 90% protection level

	Portfolio Synthetic Put	Portfolio Protective Put	Portfolio CPPI	Portfolio Stop Loss	Portfolio Pure Stocks	Portfolio Pure Cash	Portfolio 50:50 Buy & Hold
Panel A: Risk-free rate = 3,5%							
Mean p.a.	10,32%	13,23%	6,52%	11,16%	12,33%	3,56%	7,95%
Volatility p.a.	17,06%	18,75%	7,54%	20,12%	20,09%	-	10,04%
LPM0	33,86%	28,59%	18,05%	36,08%	28,59%	-	21,97%
LPM1	2,18%	2,00%	0,37%	3,33%	2,90%	-	1,00%
√LPM2	4,21%	4,18%	1,09%	5,83%	6,82%	-	2,70%
RTS1	4,7302	6,6163	17,3820	3,3520	4,2556	-	7,9443
RTS2	2,4489	3,1639	5,9802	1,9160	1,5132	-	2,7564
Omega	5,7302	7,6163	18,3820	4,3520	5,2556	-	8,9443
CPT value	3,6587**	5,3032**	3,6607**	3,2812**	2,5635	3,0582	2,9330
Panel B: Risk-free rate = 5,5%							
Mean p.a.	10,98%	13,23%	8,14%	11,61%	12,33%	5,65%	8,99%
Volatility p.a.	17,35%	18,75%	8,28%	19,92%	20,09%	-	10,04%
LPM0	32,41%	28,59%	13,27%	34,41%	28,59%	-	18,58%
LPM1	2,09%	2,00%	0,26%	3,10%	2,90%	-	0,79%
√LPM2	4,13%	4,18%	0,88%	5,60%	6,82%	-	2,33%
RTS1	5,2560	6,6201	31,4803	3,7386	4,2556	-	11,4031
RTS2	2,6561	3,1657	9,1946	2,0734	1,5132	-	3,6439
Omega	6,2560	7,6201	32,4803	4,7386	5,2556	-	12,4031
CPT value	4,0567**	5,3045**	4,8124**	3,6441**	2,5635	4,5923	3,8066

* The test statistic is significant at the 5% level

** The test statistic is significant at the 1% level

Basically, the results of the Monte Carlo simulations of the MSCI USA index are quite similar. The higher risk-free rate does not alter the annual mean returns as much as in the case of the Monte Carlo simulations with a 100% protection level (Table 9). However, the impact on CPT values is once more significant. Both, the synthetic put strategy and the stop loss strategy yield lower CPT values than the cash investment (4.0567 and 3.6441 vs. 4.5923, respectively) whereas the stop loss portfolio insurance strategy is even dominated by the buy and hold strategy regarding its CPT value (3.6441 vs. 3.8066). A paired t-test reveals that all differences are statistically significant at the 1% level.

Table 13: Monte Carlo simulation results MSCI World: Varying the risk-free rate, 90% protection level

	Portfolio Synthetic Put	Portfolio Protective Put	Portfolio CPPI	Portfolio Stop Loss	Portfolio Pure Stocks	Portfolio Pure Cash	Portfolio 50:50 Buy & Hold
Panel A: Risk-free rate = 3,5%							
Mean p.a.	9,46%	11,61%	6,02%	10,13%	10,91%	3,56%	7,24%
Volatility p.a.	15,36%	16,65%	6,43%	17,77%	17,73%	-	8,86%
LPM0	32,27%	28,38%	16,10%	33,70%	28,38%	-	21,10%
LPM1	2,02%	1,90%	0,30%	2,94%	2,59%	-	0,86%
√LPM2	4,06%	4,03%	0,95%	5,42%	6,14%	-	2,37%
RTS1	4,6928	6,1143	19,8576	3,4411	4,2070	-	8,4328
RTS2	2,3268	2,8822	6,3662	1,8693	1,7771	-	3,0509
Omega	5,6928	7,1143	20,8576	4,4411	5,2070	-	9,4328
CPT value	3,1134**	4,4291**	3,3679**	2,8588**	2,1776	3,0582	2,7377
Panel B: Risk-free rate = 5,5%							
Mean p.a.	10,01%	11,61%	7,60%	10,46%	10,91%	5,65%	8,28%
Volatility p.a.	15,60%	16,65%	7,09%	17,59%	17,73%	-	8,86%
LPM0	31,04%	28,38%	11,35%	32,42%	28,38%	-	17,42%
LPM1	1,94%	1,90%	0,20%	2,76%	2,59%	-	0,66%
√LPM2	4,01%	4,03%	0,76%	5,21%	6,14%	-	2,01%
RTS1	5,1463	6,1168	37,7706	3,7952	4,2070	-	12,6095
RTS2	2,4948	2,8834	10,0560	2,0061	1,7771	-	4,1164
Omega	6,1463	7,1168	38,7706	4,7952	5,2070	-	13,6095
CPT value	3,4367**	4,4297**	4,4891**	3,1519**	2,1776	4,5923	3,6161

* The test statistic is significant at the 5% level
** The test statistic is significant at the 1% level

Once more, a higher risk-free rate does not alter the annual mean returns as much as in the case of the Monte Carlo simulations of the MSCI World index at a 100% protection level (Table 10). However, since the MSCI World index provides the lowest risk premium and lowest volatility of all MSCI indices analyzed, the impact on the CPT values of the portfolio insurance strategies is devastating. In this case, all portfolio insurance strategies yield lower CPT values than the money market investment, whereas the synthetic put strategy and the stop loss strategy exhibit lower CPT values than the buy and hold investment (3.4367 and 3.1519 vs. 3.6161, respectively). Again, a paired t-test reveals that all differences are statistically significant at the 1% level. Hence, it seems that, when the volatility of stock market returns is relatively low, the positive impact of a higher risk-free rate cannot compensate at all for the negative impact of a lower protection level.

When comparing the results of the Monte Carlo simulations it seems that, although a higher risk-free rate positively influences CPT values, it cannot completely offset the negative impact of a lower protection level. Since the money market investment is even more attractive at a higher risk-free rate and earns an annual mean return without any loss potential, the attractiveness of the portfolio insurance strategies crucially depends on the choice of the protection level, at least from a CPT investor´s point of view. This is even more pronounced for the synthetic put portfolio insurance strategy as it exhibits significantly lower CPT values than the cash investment, whereas the stop loss portfolio insurance strategy is even dominated by the buy and hold investment regarding its CPT value. This is observable in all Monte Carlo simulations with a lower protection level and a higher risk-free rate. Additionally, if the volatility of the stock market returns is relatively low but the risk-free rate is at a higher level, it seems that an investor with CPT preferences favors the cash investment without any loss potential over all portfolio insurance strategies that do not provide a full capital guarantee (Table 13). Again, this can be explained by the high degree of loss aversion which is additionally pronounced at a higher risk-free.

4.3.3 Varying the CPPI multiplier

Besides, the quality of the CPPI portfolio insurance strategy crucially depends on the respective multiplier since its inverse indicates the maximum sudden loss in the risky asset that may occur without violating the desired floor. However, a higher multiplier leads to higher portfolio proportions in the risky asset, thereby increasing the downside risk. Although this simultaneously increases the return potential of the CPPI portfolio insurance strategy, it is unclear if a higher multiplier can compensate for the higher downside risk. Therefore, as another battery of robustness tests, the Monte Carlo simulations are repeated with a multiplier of 10, meaning that the risky asset can lose at most 10% without violating the floor.

Table 14: Monte Carlo simulation results MSCI Europe: Varying the CPPI multiplier

	Portfolio CPPI m = 2,5	Portfolio CPPI m = 10	Portfolio CPPI m = 2,5	Portfolio CPPI m = 10	Portfolio Pure Stocks	Portfolio Pure Cash	Portfolio 50:50 Buy & Hold
Panel A: Risk-free rate = 3,5%	Protection level = 100%		Protection level = 90%				
Mean p.a.	4,32%	6,56%	6,46%	10,43%	12,24%	3,56%	7,90%
Volatility p.a.	2,18%	12,43%	8,35%	20,79%	22,00%	-	11,00%
LPM0	0,00%	10,25%	21,58%	43,12%	31,03%	-	24,64%
LPM1	0,00%	0,07%	0,50%	3,35%	3,50%	-	1,26%
√LPM2	0,00%	0,41%	1,31%	5,45%	7,87%	-	3,19%
RTS1	-	91,7238	13,0465	3,1093	3,4968	-	6,2918
RTS2	-	15,9186	4,9513	1,9151	1,2490	-	2,2908
Omega	-	92,7238	14,0465	4,1093	4,4968	-	7,2918
CPT value	3,9207**	5,3568**	3,5611**	3,0622	1,9047	3,0582	2,5872
Panel B: Risk-free rate = 5,5%	Protection level = 100%		Protection level = 90%				
Mean p.a.	6,52%	8,61%	8,08%	10,98%	12,24%	5,65%	8,95%
Volatility p.a.	3,28%	14,63%	9,17%	20,77%	22,00%	-	11,00%
LPM0	0,00%	9,43%	16,55%	41,37%	31,03%	-	21,20%
LPM1	0,00%	0,09%	0,36%	3,19%	3,50%	-	1,02%
√LPM2	0,00%	0,51%	1,08%	5,29%	7,87%	-	2,79%
RTS1	-	96,2299	22,6205	3,4443	3,4968	-	8,8032
RTS2	-	17,0384	7,4522	2,0732	1,2490	-	2,9916
Omega	-	97,2299	23,6205	4,4443	4,4968	-	9,8032
CPT value	5,6475**	6,4392**	4,7190	3,4264**	1,9047	4,5923	3,4696

* The test statistic is significant at the 5% level

** The test statistic is significant at the 1% level

As expected, the annual mean return and the downside risk increase with a higher multiplier which is observable for both interest rates. However, the performance of the CPPI portfolio insurance strategy depends as well on the respective protection level. With a risk-free rate of 3.5%, the probability of earning negative returns is especially pronounced when implementing a protection level of 90% and a multiplier of 10 (LPM_0 43.12%). Additionally, since the multiplier determines the proportion of the portfolio that is invested in the risky asset, the shortfall deviation significantly increases the higher the multiplier and the respective protection level, being again at its highest value with a multiplier of 10 and a protection level of 90% ($\sqrt{LPM_2}$ 5.45%). Consequently, the CPPI strategy is dominated by both, the buy and hold investment and partly by the stock investment regarding its risk-reward ratios. However, the decisive question is how these findings compare when the analysis is based on CPT values. Surprisingly, the CPPI strategy yields the highest CPT value when implemented with a multiplier of 10 and a protection level of 100% (5.3568) but the lowest one when implemented with the same multiplier at a protection level of 90% (3.0622). In the latter case, the CPPI portfolio insurance strategy exhibits only a slightly higher CPT value than the money market investment (3.0622 vs. 3.0582) which is not even statistically significant at the 5% level. At a higher risk-free rate, however, the result is more pronounced. The CPPI strategy exhibits once more the highest shortfall probability (LPM_0 41.37%) and shortfall deviation

($\sqrt{LPM_2}$ 5.29%) when implemented with a multiplier of 10 at the 90% protection level. However, at a higher risk-free rate, the risk-reward ratios slightly improve, resulting in the dominance of the buy and hold investment only. Regarding its CPT values, the CPPI strategy yields the highest one at the 100% protection level and a multiplier of 10 (6.4392) but the lowest one when implemented with the same multiplier at a protection level of 90% (3.4264). In this case, the CPPI portfolio insurance strategy is dominated by both, the cash market investment and the buy and hold strategy regarding its CPT values (3.4264 vs. 4.5923 and 3.4696, respectively). As a paired t-test reveals, the difference in CPT values of the CPPI portfolio insurance strategy and the money market investment (being once more the best performing benchmark strategy in terms of its CPT values) is statistically significant at the 1% level.

Table 15: Monte Carlo simulation results MSCI USA: Varying the CPPI multiplier

	Portfolio CPPI m = 2,5	Portfolio CPPI m = 10	Portfolio CPPI m = 2,5	Portfolio CPPI m = 10	Portfolio Pure Stocks	Portfolio Pure Cash	Portfolio 50:50 Buy & Hold
Panel A: Risk-free rate = 3,5%	Protection level = 100%		Protection level = 90%				
Mean p.a.	4,33%	6,78%	6,52%	10,85%	12,33%	3,56%	7,95%
Volatility p.a.	1,96%	11,59%	7,54%	19,33%	12,05%	-	6,08%
LPM0	0,00%	11,58%	18,05%	31,16%	48,57%	-	48,08%
LPM1	0,00%	0,10%	0,37%	2,33%	0,42%	-	0,21%
√LPM2	0,00%	0,51%	1,09%	4,52%	0,76%	-	0,38%
RTS1	-	69,8608	17,3820	4,6634	0,1093	-	0,1431
RTS2	-	13,2531	5,9802	2,3989	0,0579	-	0,0762
Omega	-	70,8608	18,3820	4,7572	1,1242	-	1,1508
CPT value	4,7190**	5,1567**	3,6607**	3,2735**	2,5635	3,0582	2,9330
Panel B: Risk-free rate = 5,5%	Protection level = 100%		Protection level = 90%				
Mean p.a.	6,54%	8,84%	8,14%	11,28%	12,33%	5,65%	8,99%
Volatility p.a.	2,96%	13,69%	8,28%	19,24%	12,05%	-	6,01%
LPM0	0,00%	11,05%	13,27%	37,03%	48,57%	-	47,80%
LPM1	0,00%	0,13%	0,26%	2,74%	0,42%	-	0,21%
√LPM2	0,00%	0,64%	0,88%	4,90%	0,76%	-	0,38%
RTS1	-	70,1924	31,4803	4,1119	0,1093	-	0,1636
RTS2	-	13,8441	9,1946	2,3028	0,0579	-	0,0872
Omega	-	71,1924	32,4803	5,1119	1,1242	-	1,1713
CPT value	5,7297**	6,1878**	4,8124**	3,6048**	2,5635	4,5923	3,8066

* The test statistic is significant at the 5% level
** The test statistic is significant at the 1% level

Basically, the Monte Carlo simulations of the MSCI USA index lead to the same conclusions. For both interest rate levels, the annual mean return as well as the downside risk increase when the multiplier is increased. With a risk-free rate of 3.5%, the probability of earning negative returns is especially pronounced when implementing a protection level of 90% and a multiplier of 10 (LPM_0 31.16%). Again, the shortfall deviation significantly increases the higher the multiplier and the respective protection level ($\sqrt{LPM_2}$ 4.52%). But in contrast to the Monte Carlo simulation of the MSCI Europe index (Table 14), the CPPI portfolio insurance strategy significantly dominates the passive stock market investment as well as the buy and hold investment regarding its risk-reward ratios. When the analysis is based on CPT values, the CPPI strategy yields once more the highest CPT value when implemented with a multiplier of 10 and a protection level of 100% (5.1567) but the lowest one when implemented with the same multiplier at a protection level of 90% (3.2735). However, the CPPI portfolio insurance strategy significantly dominates the money market investment (being once more the best performing benchmark strategy regarding its CPT value) at the 1% level. At a higher risk-free rate, the result is even more pronounced. Again, implementing the CPPI strategy with a multiplier of 10 leads to the highest CPT value at the 100% protection level (6.1878) but the lowest one when implemented with the same multiplier at a protection level of 90% (3.6048). In the latter case, the CPPI portfolio insurance strategy is once more dominated by both, the cash market investment and the buy and hold strategy regarding its CPT values (3.6048 vs. 4.5923 and 3.8066, respectively), although it exhibits significantly better risk-reward ratios than the benchmark portfolios. As a paired t-test reveals, all differences between the money market investment and the CPPI portfolio insurance strategy are statistically significant at the 1% level.

Table 16: Monte Carlo simulation results MSCI World: Varying the CPPI multiplier

	Portfolio CPPI m = 2,5	Portfolio CPPI m = 10	Portfolio CPPI m = 2,5	Portfolio CPPI m = 10	Portfolio Pure Stocks	Portfolio Pure Cash	Portfolio 50:50 Buy & Hold
Panel A: Risk-free rate = 3,5%	Protection level = 100%		Protection level = 90%				
Mean p.a.	4,20%	6,34%	6,02%	9,85%	10,91%	3,56%	7,24%
Volatility p.a.	1,68%	9,92%	6,43%	17,07%	10,79%	-	5,42%
LPM0	0,00%	13,31%	16,10%	36,03%	48,55%	-	48,01%
LPM1	0,00%	0,14%	0,30%	2,60%	0,38%	-	0,19%
√LPM2	0,00%	0,64%	0,95%	4,81%	0,68%	-	0,34%
RTS1	-	46,5519	19,8576	3,7946	0,1103	-	0,1484
RTS2	-	9,8950	6,3662	2,0491	0,0584	-	0,0790
Omega	-	47,5519	20,8576	4,7946	1,1236	-	1,1552
CPT value	3,8472**	4,5160**	3,3679**	2,67120**	2,1776	3,0582	2,7377
Panel B: Risk-free rate = 5,5%	Protection level = 100%		Protection level = 90%				
Mean p.a.	6,35%	8,27%	7,60%	10,23%	10,91%	5,65%	8,28%
Volatility p.a.	2,53%	11,94%	7,09%	17,02%	10,79%	-	5,36%
LPM0	0,00%	13,25%	11,35%	34,70%	48,55%	-	47,69%
LPM1	0,00%	0,19%	0,20%	2,47%	0,38%	-	0,19%
√LPM2	0,00%	0,84%	0,76%	4,69%	0,68%	-	0,34%
RTS1	-	43,8283	37,7706	4,1352	0,1103	-	0,1715
RTS2	-	9,8574	10,0560	2,1832	0,0584	-	0,0914
Omega	-	44,8283	38,7706	5,1352	1,1236	-	1,1784
CPT value	5,5055**	5,4164**	4,4891**	2,9429**	2,1776	4,5923	3,6161

* The test statistic is significant at the 5% level

** The test statistic is significant at the 1% level

Generally, the Monte Carlo simulations of the MSCI World index lead to the same results. Both, the annual mean return and the downside risk increase when implementing the CPPI portfolio insurance strategy with a higher multiplier. With a risk-free rate of 3.5%, the probability of earning negative returns is once more particularly pronounced when implementing a protection level of 90% and a multiplier of 10 (LPM_0 36.03%). Besides, the shortfall deviation significantly increases as well the higher the multiplier and the respective protection level ($\sqrt{LPM_2}$ 4.81%). However, the CPPI strategy dominates both, the buy and hold investment and even the stock investment regarding its risk-reward ratios. When the analysis is based on CPT values, the CPPI strategy again yields the highest CPT value when implemented with a multiplier of 10 and a protection level of 100% (4.5160) but the lowest one when implemented with the same multiplier at a protection level of 90% (2.6712). In the latter case, the CPPI strategy is once more dominated by the cash investment and the buy and hold investment regarding its CPT value (2.6712 vs. 3.0582 and 2.7377, respectively). As a paired t-test reveals, the difference of the CPT values of the CPPI portfolio insurance strategy and that of the cash investment (being once more the best performing benchmark strategy regarding its CPT value) is statistically significant at the 1% level. At a higher risk-free rate, however, the result is more pronounced. Again, implementing the CPPI strategy with a multiplier of 10 leads to the highest CPT value at the 100% protection level (5.4164) but the lowest one when implemented with the same multiplier at a protection level of 90% (2.9429). In the latter case, the CPPI portfolio insurance strategy is again dominated by both, the cash market investment and the buy and hold strategy regarding its CPT values (2.9429 vs. 4.5923 and 3.6161, respectively), although it exhibits significantly better risk-reward ratios than the benchmark portfolios. All differences are statistically significant at the 1% level.

When comparing the results of all Monte Carlo simulations in regard to the CPPI strategy, the following pattern is observable: The higher the risk-free rate, the higher the CPT values of the CPPI portfolio insurance strategy. This observation can once more be explained by lower opportunity costs since the risk premium of the portfolio insurance strategy is lower as the risk-free rate is higher. Furthermore, despite of a lower return potential, it seems more beneficial for a CPT investor to implement the CPPI strategy with a 100% protection level. This finding can again be explained by the high degree of loss aversion. However, the choice of the protection level crucially depends on the respective multiplier. In contrast to the finding of Dichtl and Drobetz (2010) that, at a lower protection level, any multiplier will lead to the inferiority of the CPPI strategy regarding its CPT values, it seems that, at a higher protection level, the CPPI strategy should be implemented as aggressive as possible (high multiplier), whereas at a lower protection level, it should be implemented as least as aggressively as possible (low multiplier).

5. Conclusion

Almost all elements of traditional finance theory with its emphasis on rationality were developed before the 1980´s. But since then, financial markets went through a drastic change due to the liberalization of capital markets, financial innovation and improvements made in information technology. New markets were created in which options and futures were traded, thereby facilitating the implementation of portfolio insurance strategies. According to a tremendous amount of research, investors do not always behave rationally when forming their preferences and systematically fail to update their beliefs correctly, thereby relying on heuristics rather than on rational behavior. Since it seems that human behavior is far more complex than assumed by traditional finance models, perhaps the new behavioral models can serve to understand investor behavior better than the traditional models based on rationality.

Since traditional finance still struggles to provide an explanation for the unbroken popularity of portfolio insurance strategies, this thesis tries to explain the attractiveness of portfolio insurance strategies in a behavioral finance context. The findings reveal that the unbroken popularity of portfolio insurance strategies can be explained within Tversky and Kahneman´s cumulative prospect theory (CPT). More precisely, since CPT investors are more attracted by the avoidance of losses than the achievement of higher returns, the attractiveness of portfolio insurance strategies can be justified by the high degree of loss aversion. Additionally, investors tend to overestimate the probability of extreme but less likely events which further contributes to that attractiveness. Overall, the findings are robust and indicate that the synthetic put portfolio insurance strategy, the protective put portfolio insurance strategy, the CPPI strategy and the stop loss portfolio insurance strategy provide a beneficial investment strategy for investors with CPT preferences. Furthermore, the analysis provides additional insights on how a portfolio insurance strategy should be designed in order to meet the CPT investor´s preferences as good as possible. Despite of a lower return potential, a higher protection level seems preferable for an investor with CPT preferences. Moreover, implementing the portfolio insurance strategies with a lower protection level leads to an overall reduction in the attractiveness from a CPT investor´s point of view which can only be partly compensated by the positive impact of lower opportunity costs. This is particularly pronounced for the protective put strategy and the stop loss strategy since they seem only half as attractive for a CPT investor when implemented with a lower protection level. Furthermore, at a higher risk-free rate but relatively low volatility of stock market returns, an investor with CPT preferences favors the cash investment without any loss potential over all portfolio insurance strategies that do not provide a full capital guarantee. Additionally, the attractiveness of the CPPI portfolio insurance strategy crucially depends on the trade-off between the respective protection level and the multiplier of the portfolio insurance strategy. At a higher protection level, the CPPI strategy should be implemented as aggressive as possible (higher multiplier) whereas at a lower protection level, it should be implemented as least as aggressive as possible (lower multiplier).

However, in future research it would be interesting to examine the portfolio insurance strategies under different parameter settings. Of particular interest is the rebalancing frequency since individual investors might monitor their portfolio insurance strategy only once a month or even not that often due to the lack of time or simply for avoiding transaction costs. Additionally, different time horizons would be equally interesting since Dierkes et al. (2010) find strong horizons effect under the CPT framework. According to their results, the pure bond portfolio (which is equivalent to the cash investment) is prefered in the short run which is consistent with the findings of this thesis, but the stock portfolio is prefered in the long run. Annother issue that can be addressed in future work is the analysis of portfolio insurance strategies based on real financial markets data as Monte Carlo simulations provide only a limited model of financial markets. Dichtl and Drobetz (2010) perform historical simulations using German financial markets data and compare the results with those of their Monte Carlo simulations. They find that the time series characteristics of stock market returns negatively impact CPT values, resulting in higher CPT values in the Monte Carlo simulations. However, this comparison is only done at the 100% protection level. Therefore it would be interesting if the time series characteristics of stock market returns lead to different conclusions at the 90% protection level.

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Annex

Abstract (English)

Almost all elements of traditional finance theory with its emphasis on rationality were developed before the 1980´s. But since then, financial markets went through a drastic change due to the liberalization of capital markets, financial innovations and improvements made in information technology. Additionally, more and more investors entered the stock markets, being attracted by its high return potential. As a vast amount of empirical research suggests, investors do not always behave rationally and systematically fail to update their beliefs. Since it seems that human behavior is far more complex than assumed by traditional finance models, the new behavioral models can serve to understand market reactions better than the traditional models based on rational behavior. Therefore, the overriding objective of this thesis is to explain the unbroken popularity of portfolio insurance strategies in a behavioral finance context. More precisely, the attractiveness of four portfolio insurance strategies, the synthetic put strategy, protective put strategy, constant proportion portfolio insurance (CPPI) strategy and the stop loss strategy, together with simple benchmark strategies are examined within the framework of cumulative prospect theory (CPT). In order to derive a full distribution of outcomes, Monte Carlo simulations generate 100.000 random paths for daily stock prices on the basis of a Geometric Brownian motion. The findings reveal that portfolio insurance strategies provide an attractive investment strategy for an investor with CPT preferences but crucially depend on the respective protection level, the risk premium and the volatility of stock market returns. Additionally, the attractiveness of the CPPI strategy crucially depends on the trade-off between the respective protection level and the aggressiveness of the portfolio insurance strategy.

Abstract (German)

Beinahe alle Elemente der traditionellen Finanztheorie mit ihrem Schwerpunkt auf rationale Investoren wurden vor den 1980er Jahren entwickelt. Allerdings haben sich die Finanzmärkte danach drastisch verändert, ausgelöst durch die Liberalisierung der Märkte, der Entwicklung von Finanzinnovationen und aufgrund von Verbesserungen im Bereich der Informationstechnologie. Zusätzlich animierte das hohe Renditepotenzial der Aktienmärkte immer mehr Personen dazu an den Finanzmärkten zu investieren. Mittlerweile existieren jedoch zahlreiche empirische Untersuchungen die belegen, dass sich Investoren nicht immer rational verhalten und systematisch kognitive Fehler begehen. Da es so scheint, dass das menschliche Verhalten weit komplexer ist als von der traditionellen Finanztheorie angenommen, bieten die neuen Verhaltensmodelle der Behavioral Finance möglicherweise eine bessere Erklärung für die beobachteten Marktanomalien der Finanzmärkte als die traditionellen auf Rationalität basierenden Finanzmodelle. Daher ist das vorrangige Ziel dieser Arbeit die ungebrochene Popularität der Portfolioversicherungen anhand der Behavioral Finance zu erklären. Dabei wird die Attraktivität von vier selektiv ausgewählten Portfolioversicherungen, der Protective Put Portfolioversicherung, der Synthetic Put Portfolioversicherung, der Constant Proportion Portfolioversicherung (CPPI) und der Stop Loss Portfolioversicherung, gemeinsam mit einfachen Benchmark-Strategien im Rahmen der Cumulative Prospect Theory (CPT) untersucht. Um ein möglichst vollständiges Bild über das Verhalten der Portfolioversicherung zu gewährleisten, werden Monte Carlo Simulationen eingesetzt, welche 100,000 zufällig erzeugte Aktienpfade auf Basis einer Geometrischen Brownschen Bewegung generieren. Wie die Ergebnisse belegen, bieten Portfolioversicherungen eine attraktive Anlagestrategie für einen Investor mit CPT Präferenzen. Allerdings hängt diese Attraktivität entscheidend vom jeweiligen Versicherungsschutz, der Risikoprämie und der Volatilität der Aktienkurse ab. Im Falle der CPPI Portfolioversicherung hängt die Attraktivität für einen CPT Investor darüber hinaus entscheidend von der gegenseitigen Abstimmung des Versicherungsschutzes und der Aggressivität der Portfolioversicherung ab.

Curriculum Vitae

Personal Information

Name	Margit Steiner
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Work experience

01/2001 – 08/2006 Sparkasse Pottenstein N.Ö. 2563 Pottenstein Austria	**2005 Employee Loan department** Foreign currency loans, commercial loans, residential mortgage loans, interest rate changes **2004 Assistant manager Finance and Controlling department** Controlling, internal reporting, supervisory reporting to the European Central Bank and Austria National Bank, exchange dealings, foreign currency loans **2001 Employee Finance and Controlling department** Bookkeeping, foreign remittance, scanning and archiving
04/2000 – 01/2001 Seminarhotel Hernstein 2560 Hernstein Austria	**Employee** Customer service
05/1999 – 10/1999 Spain	**Stay abroad**
08/1997 – 04/1999 Baumit Wopfinger 2754 Waldegg Austria	**Employee Complaints and Billing department** Customer service, billings, complaints, archiving
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Education

Since October 2009 University of Vienna Faculty of Business Studies 1210 Vienna Austria	Master of International Business Studies Winter 2010 Semester abroad in Montréal, Canada
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09/1992 – 06/1997 Höhere Bundeslehranstalt für wirtschaftliche Berufe 2500 Baden Austria	Commercial and Touristic education A-levels

Professional Qualifications

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09/2005	S-Cyber School Controlling, excellent
Computer Skills	Microsoft Office (incl. Excel VBA), excellent SAP E3P, Html, Java, SQL, good
Awards and honors	**2011 – 2010 Scholarship Land Niederösterreich** Excellent academic achievements, GPA below 2.0 **2007 – 2010 Scholarship of the University of Vienna** Excellent academic achievements, GPA below 2.0 **2010 Best of the Best** Bachelor Studies above average **2008 Special scholarship of the University of Vienna** Excellent academic achievements, GPA below 2.0
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