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Assessing goal-based performance with structured products

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Introduction

In the fast growing realm of portfolio management, the most known and utilized framework, Modern Portfolio Theory (MPT), has traditionally been the foundational model for asset allocation and portfolio construction. Although its popularity, in the past decades several scholars have started doubting the effectiveness and quality of the results obtained through this method. As we will see more into details in the following chapters, these models frequently fail to reflect the complex behaviours and preferences of real investors, because one of the key (and most deleterious) assumption made is that investors behave and manage their wealth in a rational way. Subsequently, Behavioural Portfolio Theory (BPT), firstly and "officially" introduced by , started addressing these shortcomings by highlighting the psychological and goal-driven foundations of investment decisions. Within this perspective, investors are recognised as heterogeneous agents with varied aspirations, distinct mental accounts, asymmetric risk–return attitudes, and, most importantly, they are considered more human, thus taking into account psychological biases as well.

This work in particular investigates the application of the Horizon-Asymmetry Mental Accounting (HAMA) model, introduced by Hübner and Lejeune (2021), specifically in the context of structured products. While structured products may be suboptimal from a classical risk–return perspective, their persistent popularity is often attributed to behavioural biases such as loss aversion, the preference for capital protection, and the attraction to lottery-type "wins".

The main goal of this research is to evaluate the goal-based performance of structured products through the lens of the HAMA model. By simulating a range of market environments and investor types, the study assesses four commonly used structured strategies: protective puts, bonus certificates, covered calls, and collars, all across varying investment horizons and risk preferences. This approach not only sheds light on the behavioural appeal of these instruments but also demonstrates the practical value of the HAMA model in aligning structured product strategies with distinct investor financial (and life) objectives.

This thesis is structured to guide the reader through both the theoretical foundations and the empirical analysis of structured products in portfolio management. The work opens with a brief introduction to Modern Portfolio Theory and its comparison with Behavioral Portfolio Theory, setting the stage by discussing both the fundamental principles and the main critiques that have emerged in the last decades. After that, the second chapter constitutes an in depth literature review of BPT models that were introduced in the last thirty years. Building on this, the third chapter is then dedicated to specifically the HAMA Model, which forms the methodological core of the study. The following section goes then into details on the presentation and implementation of the model itself. In the same part, there will be presented the empirical findings and discussion on them. Furthermore, a comparative analysis has been carried out, with the

intention of giving to the reader a broad and comprehensive view of the research. The thesis then concludes with which a brief summarize of the main findings and discusses the limitations of the work, and proposes possible directions for the future research.

Section 1

Modern Portfolio Theory vs Behavioral Portfolio Theory

1.1 Modern Portfolio Theory

Since the first introduction by Markowitz (1952), Modern Portfolio Theory has been largely considered the cornerstone of portfolio construction by financial advisors, asset managers, and scholars. Its key principle is that it relies on the mean-variance optimization framework by assuming that investors behave in a rational manner and aim to maximize portfolio returns for a pre-defined level of risk. Risk, within this paradigm, is traditionally measured with the standard deviation, assuming that these are normally distributed. Consequently, portfolio performance is often assessed and carried out to the final clients using metrics derived from this assumption; one of these such metrics is, for example, the Sharpe Ratio (Sharpe, 1966).

1.2 Limitations and Critiques to Modern Portfolio Theory

Over the years, several academics have started to point out the limitations of the mean-variance framework. In order to better understand the drawbacks, we need first to make one step back: as outlined by Markowitz (1959), Modern Portfolio Theory leads to the maximization of the following expected utility function:

$$U = E(r_p) - \frac{1}{2}\gamma\sigma^2 \quad (1.1)$$

where γ stands for the risk aversion coefficient. As emphasised by Allais (1953), both investors and financial advisors often find it challenging to estimate the risk aversion coefficient in a precise way, whether through standard questionnaires or other methodologies. This difficulty commonly causes mis-specification, as a lack of intuitive understanding and strong sensitivity to framing effects can distort the estimation process. Consequently, such mis-specification may lead to portfolios that are misaligned with investors' actual expectations and preferences. To address these shortcomings, some scholars have proposed target volatility models as an alternative means of capturing investor risk preferences. In this context, Hübner (2024) provides a comprehensive

analysis of volatility-targeting models, which are specifically designed to maintain portfolio risk at a predefined level of volatility (typically expressed as standard deviation). Here, the so-called “volatility budget” serves as a substitute for the traditional risk aversion coefficient, providing a more intuitive and investor-friendly parameter to describe risk appetite. Although this approach may simplify the estimation of investor risk preference, Hübner identifies several critical limitations that undermine this methodology. Firstly, a “volatility mismatch penalty” can arise when the actual portfolio volatility deviates from the target, resulting in potentially severe impacts on portfolio performance. This penalty is most pronounced for defensive investors and in periods of elevated market risk premia, potentially leading to significant utility loss. Furthermore, target volatility models can yield suboptimal allocations despite fluctuating market conditions. If realised market risk premia differ from expectations, portfolios with constant volatility constraints may become either excessively risky during periods of low premia or overly conservative when risk-taking is most rewarded. Finally, when applied to active portfolios that generate strong performance, the model’s risk constraints can prevent the attainment of optimal leverage, thereby limiting potential value creation for the investor.

Beyond these analytical limitations related to estimation risk, behavioural factors add further complexity to portfolio construction. In this regard, Thaler (1985) introduced mental accounting theory, demonstrating that investors tend to divide their wealth into separate mental accounts, each dedicated to a particular goal, such as retirement savings or future home purchases. Statman (1999) subsequently developed this concept by illustrating that these mental accounts often follow a pyramidal structure, with investors prioritising certain objectives over others. For instance, while some funds are allocated to secure, low-risk investments to provide financial safety, other funds may be invested in riskier assets to pursue long-term growth. Building on these behavioural insights, Brunel (2003) proposed a behavioural allocation framework aiming to align portfolio construction more closely with an investor’s individual goals and needs. This framework will be examined in much more detail in the following chapter.

Although this approach better reflects investor preferences, incorporating a mental accounting structure into the mean-variance framework significantly complicates the portfolio optimisation process. Whereas traditional models like Modern Portfolio Theory require the estimation of a single risk aversion coefficient, the mental accounting framework necessitates multiple risk aversion coefficients—one for each mental account—thereby exacerbating estimation challenges and increasing model complexity.

Despite these advances, a major limitation of MPT remains its foundational assumption of investor rationality. Empirical studies demonstrate that investors are subject to various cognitive biases that significantly influence their investment decision-making process. For instance, overconfidence leads investors to overestimate their capabilities and underestimate risks, often resulting in suboptimal portfolio performance, as discussed in Ritter (2003). Such overconfidence directly contradicts MPT’s presumption that investors make unbiased risk-return assessments. Furthermore, the disposition effect, described by Benartzi and Thaler (2001), is the bias that explains the investors’ tendency to sell winning assets prematurely while holding onto losing assets; this behaviour, from a psychological perspective, is usually driven by the desire to realise gains and avoid the upset-ness deriving from the recognition of financial losses. This bias is thus in clear conflict with the mean-variance optimisation method, which is indifferent to the timing of gains or losses. In addition to these tendencies, Samuelson (1971) high-

lighted investors' irrational behaviour by showing their frequent rejection of favourable long-term investments due to short-term risk concerns, a phenomenon that is known as myopic loss aversion. This finding helps explain why many investors avoid strategies like equity investing, despite higher long-term returns. Such behavioural patterns further challenge MPT's single-period optimisation assumptions, underscoring the need for models that incorporate multi-period decision-making and behavioural factors.

Section 2

Literature Review

2.1 Behavioural Portfolio Theory Models

It is in this context that Behavioural Portfolio Theory emerged and became popular, offering a more behaviourally realistic framework for understanding portfolio construction. Unlike MPT, which uses standard deviation as a proxy for risk, BPT defines risk as the probability of failing to meet an investment goal; this is an evident and crucial shift that results in a more intuitive and practically relevant measure for many investors, as discussed previously.

The first formal articulation of BPT was provided by Shefrin and Statman (2000), who argued that investors may display both risk aversion and risk seeking simultaneously. Their central insight was that by allowing investors to pursue multiple aspirations and subdivide their wealth into separate mental accounts, it becomes possible to explain behaviours that contradict the “two-fund separation” principle, that is central to MPT. While traditional theory cannot account for the simultaneous purchase of insurance against small risks and engagement in high-risk investments, Behavioural Portfolio Theory is able to resolve this paradox by acknowledging individuals’ desire both to protect themselves from catastrophic losses and to pursue large potential gains. These insights are consistent with the insurance-lottery puzzle first described by Friedman and Savage (1948).

Building on Shefrin and Statman’s foundational work, subsequent researchers have refined and expanded BPT. Notably, Brunel (2003) proposed that investment decisions should be structured around an investor’s specific financial objectives, rather than being focused solely on risk and return optimisation. To this end, he introduced a framework in which portfolios are segmented according to four primary investment goals: liquidity, income, capital preservation, and growth. Each of these then coincides to a precise and unique mental account, which reflects differing risk tolerances and investment horizons and goals. This approach demonstrated a practical alignment between BPT and the real-world financial planning process, further validating the role of mental accounting.

The theoretical foundations of BPT have also been reinforced by empirical research. For example, Choi et al. (2009) provided empirical evidence for mental accounting by showing that investors segregate their wealth into distinct psychological categories, influencing both their savings behaviour and investment decisions. Their findings underscore the necessity of portfolio models that accommodate the ways in which investors mentally organise their assets.

Das et al. (2010; 2011) further develop the behavioural approach by demonstrating

that portfolios structured according to Behavioural Portfolio Theory do not incur an efficiency loss and, importantly, still lie on the mean-variance efficient frontier. In their 2010 paper, the authors introduce an innovative framework that unifies mental accounting with mean-variance optimisation, showing that sub-portfolios dedicated to specific thresholds of aspiration and safety can be aggregated into a single portfolio while retaining the benefits of mean-variance efficiency. In other words, even though different mental accounts might have different level of "risk preference", they can all be unite into a single portfolio, resulting into a more efficient optimisation process. Their 2011 follow-up illustrates the practical application of these concepts, enabling investors to structure portfolios that address individual goals yet remain efficient. This evidence suggests that mental accounts can be incorporated in a manner consistent with the principles of traditional Modern Portfolio Theory, while still reflecting the nuanced, goal-based preferences of investors, thus resulting in a more precise and complete model.

In the following years, several models were introduced. Among the further refinements to BPT, Das and Statman (2013)'s work contributed to this field by exploring the role of structured products in behavioural portfolios. They argued that investors optimize each mental account with the condition that the probability of not reaching the predefined threshold is minimized. This approach highlights the usage of derivative instruments (like as put and call options) for downside protection and for capturing upside potential, thus aligning portfolio construction with investors' behavioural biases toward loss aversion and aspiration.

While these advancements improved the theoretical and empirical foundation of BPT, there was still a need for a more dynamic and adaptable framework that could better reflect the evolving nature of investor preferences. On this purpose, Momen et al. (2019) introduced the so-called Collective Mental Account (CMA) model, a significant evolution of BPT. Unlike earlier models, which optimized each mental account independently, the CMA model sought to optimize total wealth holistically. This framework computed the weights of mental accounts as a proportion of total wealth while allowing for multiple constraints, such as different risk aversion levels across accounts. By incorporating these elements, the CMA model provided a more flexible and realistic representation of investor behaviour, further bridging the gap between behavioural finance and practical portfolio management.

A critical challenge in BPT research is its reliance on the assumption of normally distributed returns, which does not accurately reflect the empirical characteristics of financial markets. As demonstrated by Pfiffelmann (2016), although BPT portfolios may often sit on the efficient frontier, they tend to prompt market exit during periods of financial distress. This highlights the importance of modelling tail events within portfolio theory. To address this limitation, Alexander et al. (2017, 2020) incorporated downside risk measures and tail risk management into BPT models. Financial return distributions frequently display skewness and kurtosis, especially during market downturns. By accounting for these higher moments, Alexander and co-authors have improved the robustness of BPT, enhancing its applicability in environments where the assumption of normality fails.

A significant development in overcoming this limitation is the Horizon-Asymmetry Mental Accounting model proposed by Hübner and Lejeune (2021). This model employs a semi-parametric approach that avoids underestimating risk by moving beyond the simplistic normal distribution assumption. Crucially, the HAMA model is sensitive to the third and fourth statistical moments. Its behavioural portfolio construction

process reflects two essential features: preferences for investment horizon and gain–loss asymmetry. The authors demonstrate that risk tolerance varies with investment horizon, with long-term investors typically displaying greater risk appetite. Additionally, the model captures the asymmetric preferences investors have toward gains and losses, whereby losses are generally felt more acutely than equivalent gains, a key finding of Prospect Theory (Kahneman and Tversky, 1979). Under Prospect Theory, individuals (investors) judge the results in relation to a reference point, exhibiting risk aversion in case of gains and risk-seeking behaviour in case of losses. Tversky and Kahneman (1992) then further developed this framework through Cumulative Prospect Theory (CPT), which recognises that individuals tend to overweight small probabilities and underweight large ones, thus deviating from predictions of MPT.

Additional theories have also explored asymmetric risk preferences. For example, Gul’s (1991) disappointment aversion theory suggests that investors dislike not only losses, but also the disappointment experienced when returns fall short of expectations. Meanwhile, Roy’s (1952) Safety-First Principle posits that investors prioritise avoiding extreme downside risks over maximising returns, thereby challenging the symmetric risk–return assumption of MPT.¹ Dichtl and Drobetz (2011) argue that Modern Portfolio Theory inadequately addresses extreme risks, as their findings suggest that investors are particularly sensitive to such events. As a result, relying solely on volatility as a risk metric proves insufficient for capturing the realities of investment decision-making.

Recent progress in Behavioural Portfolio Theory has increasingly drawn on machine learning to advance portfolio optimisation. For instance, Kim et al. (2020, 2022) utilised reinforcement learning algorithms to optimise goal-based portfolios, demonstrating that adaptive strategies can outperform traditional static approaches. Their research underscores the potential of real-time, data-driven methods for behavioural portfolio construction, enabling investors to adjust portfolios dynamically in response to changing markets and shifting preferences. Similarly, Mittal et al. (2022) introduced subjective risk perception measures into BPT, acknowledging that risk tolerance reflects not only objective financial variables but also psychological factors such as overconfidence and framing effects. This personalised approach enhances the practical relevance of BPT for real-world investment scenarios.

More recently, Poddar et al. (2024) integrated BPT with the traditional Markowitz framework, with an emphasis on sustainability and risk mitigation during market downturns. They adopted Conditional Drawdown at Risk (CDaR) and Expected Regret of Drawdown (ERoD), in order to select assets that provide resilience during market downturns. CDaR captures the maximum average drawdown, while ERoD quantifies the regret associated with higher drawdowns. The authors employed these measures to construct portfolios that minimise drawdown risk while maintaining a minimum expected return. Moreover, their optimisation process incorporates ESG factors, using an ESG preference function to evaluate the utility these criteria add to portfolio composition. Taken together, these methodological advancements provide Behavioural Portfolio Theory with more prescriptive, robust, and efficient tools—particularly valuable for investment decision-making in highly volatile markets².

¹Further evidence in support of this comes from Benartzi and Thaler (1995), in which the authors solve the equity premium puzzle through a combination of loss aversion (investor dislike more losses than enjoy equivalent gains) and myopic evaluation outcomes. For further information also take a look at Lopes (1987) and Dahlquist et al (2016).

²For further models developed during the years refer to Nevins (2004), Statman (2008), Mitton and Vorkink (2007), Curtis (2004), Baptista (2012), Das et al. (2018) and Harris and Mazibas (2022)

Despite these developments, a persistent challenge in BPT research has been the need for a unified model that accommodates mental accounting, goal-based segmentation, preference asymmetries, and the non-normal characteristics of financial return distributions. The Horizon-Asymmetry Mental Accounting framework (HAMA) by Hübner and Lejeune (2021) has emerged as one of the most comprehensive solutions, integrating the best elements of previous models while addressing their limitations. By incorporating investment horizon preferences and gain-loss asymmetry, the model ensures that risk tolerance is appropriately adjusted across time. Moreover, its emphasis on tail risks makes it highly relevant for contemporary financial markets, particularly in post-crisis environments where normality assumptions are no longer viable.

2.2 The HAMA Model

As said before, the HAMA model introduced by Hübner and Lejeune (2021) has the ability to overcome the issues that were discussed in the previous chapter. In their research, the authors analysed a portfolio composed by different products (stocks and bonds) with different features, with the goal of testing the effectiveness of the model for various investors and market products. Following the same path, the aim of this work is to expand their and test the model for another type of financial assets: structured products. The need for this analysis is due to the fact that this kind of product is very popular among investments. Historically, structured products grew in popularity in the years immediately preceding the global financial crisis. This finding can be clearly noticed by looking at the FRED data (FRED, 2025) in the figure 2.1 below:



Figure 2.1: FRED data: Asset-Backed Commercial Paper Outstanding over time.

From the graph above, it is possible to affirm that asset-backed securities outstanding reached their peak in 2007; even though with the consequences of the crisis their volumes contracted sharply, since the COVID-19 pandemic they have begun to climb once again, and structured products now account for hundreds of billions of dollars in the market. Indeed, the S&P Global report show that issuance of these instruments summed up accounted for 1225 billion dollars in 2021 (S&P Global Ratings, 2024), with the United States and Europe representing the largest regional markets. Given its significant size and recent return, the structured-products market clearly demands a detailed analysis. Despite their just described popularity among retail and institutional investors, traditional financial theory, such as MPT, struggles to fully account for their widespread appeal. As a matter of fact, a growing body of research suggests that the demand for structured products is largely driven by behavioral factors. A

pivotal contribution to this discussion is offered by Hens and Rieger (2008, 2011), as well as Rieger et al. (2013), who demonstrate that structured products are often sub-optimal investments when evaluated solely on the basis of expected return and risk; as a consequence, under the assumption of rational investors, these products should not be picked. However, as previously discovered, they still remain prevalent because they satisfy specific behavioral preferences and psychological biases present that are typical for a more realistic type of investors. Going more into details, their research highlights that features like capital protection, leverage, or participation in upside potential align closely with certain investor behaviors, which can drive preferences that are not consistent with traditional portfolio theory. Kumar (2009) further expands on this idea by linking the popularity of structured products to the human propensity to gamble. According to his findings, many investors are attracted to products that offer lottery-like payoffs, even if this results into suboptimal expected return, due to a very human desire to take risks for potentially large rewards. This behavioral inclination can thus explain why structured products with skewed payoffs and high potential returns (and high riskiness) find such a strong demand. Supporting evidence is also provided by Merrill et al. (2019), who examine the behavioral mechanisms and psychological appeal underlying structured product design, and by Rieger and Hens (2012), who explore the persistence of these preferences across different markets and investor segments. With all the clarifications from the paragraph above, it appears therefore critical to carry out a study of these products and, particularly, that this analysis should be done through the lens of a model that is capable of taking into account the behavioural aspects discussed within this work.

Before delving into the analysis of structured products, it is considered appropriate to firstly introduce the HAMA model itself. The Horizon-Asymmetry Mental Accounting model extends the Mental Accounting framework by introducing two complementary dimensions that better capture investors' preferences (by taking into account typical human features and biases): the investment horizon and the gain-loss asymmetry trade-off. In the Mental Accounting setup, investors divide their wealth into sub-accounts; each goal-based account is associated with a threshold return and a maximum shortfall probability, and investors seek to maximize the expected returns subject to the constraint that the probability of missing the threshold does not surpass a chosen level of tolerance. Thus, it can be formalized as follows:

$$\max E[R_p] \text{ s.t. } \pi_p(-\lambda_m, H_m) - \gamma_m \pi_p(\lambda_m, H_m) \leq \Omega_m \quad (2.1)$$

Where (i) the parameter γ_m reflects the weight assigned to the upside potential relative to downside risk, (ii) H_m represents the time horizon for each portfolio, (iii) the deviation λ_m measures the distance from expected return, and (iv) Ω_m represents the highest tolerance probability of missing the threshold. When $\gamma_m = 0$, the model reduces to a "safety-first" situation; in other words, investors are only concerned with avoiding disastrous outcomes; this is in line with findings in Roy (1952). Furthermore, as γ_m increases, the constraint becomes laxer until it is equal to one, in which case the investor is risk neutral.

To implement HAMA in practice without imposing a specific return distribution, a semi-parametric approach is applied in the analysis. In practice, this translates into taking the "observed" probability distributions; in other words, the measures of probabilities are based on the observed frequencies of returns below and above some tolerance threshold. In order to establish the tolerance level, the parameter δ is introduced: δ

measures the maximum acceptable amount by which the return can fall short of the expected value before the investor perceives it as a "loss". Translated into practical terms, the "observed" probabilities represents the number of observations of returns that are below $\mathbb{E}[R] - \delta$ and above $\mathbb{E}[R] + \delta$. Formally, the optimization translates as follows:

$$\max_p \quad \bar{R}_P \quad (2.2)$$

$$\text{s.t.} \quad \frac{S_P^-}{S} - \eta \frac{S_P^+}{S} \leq \Omega \quad (2.3)$$

$$\text{where:} \quad S_P^- = \frac{\#\{r_i \mid r_i < \mathbb{E}[R] - \delta\}}{N} \quad (2.4)$$

$$\text{and} \quad S_P^+ = \frac{\#\{r_i \mid r_i > \mathbb{E}[R] + \delta\}}{N} \quad (2.5)$$

As pointed out by François and Hübner (2024), imposing $\eta = 0$ leads to the more "classic" optimization method according to the Modern Portfolio Theory. Overall, HAMA delivers an intuitively appealing and flexible tool for analyzing complex payoffs by capturing both temporal effects and asymmetric attitudes toward gains and losses in a unified optimization framework.

Section 3

Empirical Analysis

Assumptions

Before going through the analysis, it is essential to comprehensively explain the underlying assumptions that were made. In this study, stock prices are modelled using a Geometric Brownian Motion (hereafter, GBM), which posits a continuous-time stochastic process characterised by a constant drift and volatility. This modelling choice implies that price increments, as well as returns over infinitesimally small time intervals, are normally distributed. Both the volatility of the underlying asset and the risk-free rate are assumed constant throughout the simulation horizons. While these assumptions are somewhat stylised, they are consistent with the fundamental principles of the Black-Scholes-Merton framework, which forms the basis for the valuation of derivative instruments employed in this research. Additionally, the model presumes that the underlying stock does not pay dividends and that there are no transaction costs, taxes, or market frictions. The analysis exclusively considers European-style options, which may be exercised only at maturity. Option pricing is conducted within the Black-Scholes framework, which further assumes continuous trading, the absence of arbitrage opportunities, and perfect market liquidity. Furthermore, the internal rate of return (IRR) is calculated under the assumption that any intermediate cash flows (like coupons from bonus certificate) are reinvested at the IRR, a standard approach in financial modelling. The statistical properties of simulated return distributions are assumed to adequately represent the distributional characteristics and associated risks of the investment. Finally, the optimisation component of the analysis incorporates constraints specifically designed to manage the asymmetry of the IRR distribution, as defined by relevant parameters δ (delta), η (eta), and ω (omega), under the premise that such asymmetry control is meaningful and aligned with investor preferences and decision-making objectives. All these assumptions establish the analytical framework within which the subsequent empirical investigation will proceed.

3.1 Methodology

Now, before going through the methodology, it is worth mentioning and describing the features of the products that are under study: starting from the protective put, it is a common derivatives strategy that consists of buying a put option of an underlying asset that is under possession. Conversely, a covered call is a strategy that is formed

of a stock (underlying asset) and a short position on a call option on the same stock. Furthermore, the collar strategy is a combination of the ones described before: thus it is composed by the stock, a long position on a put option and a short position on a call option. A little more tricky is the bonus certificate: during its lifetime, if the stock price of the underlying asset never falls below a threshold (so-called barrier), the investor obtains bonus amount at maturity and, until maturity and irrespectively of the price of the stock. For this last product, the derivative component is the auto-call embedded in the product. This study, as said before, introduces a simulation-based framework for the evaluation and optimisation of option-based investment strategies, based on the assumption that stock prices follow a GBM. As outlined previously, the modelling framework assumes both constant volatility and a fixed risk-free interest rate, consistent with the foundational premises established in the preceding chapter. All analyses are conducted over multiple time horizons, discretised into monthly intervals.

The simulation process starts with the generation of stock price paths, using specified parameters for expected return, volatility, and the risk-free rate. For each product, 50,000 simulated paths were generated to ensure the robustness of the estimates. To provide a more comprehensive analysis, ten distinct stock types were simulated, in line with Hübner and Lejeune (2021). These include three stocks with Gaussian returns (featuring low, medium, and high volatility), two lottery-type stocks, two stocks with leptokurtic distributions, two skewed stocks, one glamour stock, and a one-month T-Bill. The parameters of the GBM were adjusted to reflect the particular characteristics of each stock type.

Option pricing is performed using the standard Black-Scholes formulae for European call and put options. The analysis encompasses four different structured products—covered call, protective put, collar, and bonus certificate. While the implementation details of these products vary, the first three exhibit only minor structural differences and are therefore examined collectively.

The central component of the methodology involves optimising the composition of the option positions. In particular, the number of call and put options is treated as a decision variable and is determined via a constrained optimisation process as per the HAMA model. The objective is to maximise the expected IRR of the portfolio at maturity subjected at the constraint in 2.1. In particular, the IRR is determined based on the terminal payoffs of the products and incorporates both the costs and payoffs associated with the underlying assets and the corresponding derivative instruments.

3.2 Mapping of Parameters

Before presenting the analysis of the results obtained in this study, it is essential to briefly outline the mapping methodology that was adopted. This step ensures that the interpretation of the findings is grounded in a clear understanding of the methodological framework.

A key challenge encountered when dealing with portfolio management concerns the estimation of investor-specific parameters. Just to recall, as emphasized by Allais (1953), deriving these parameters through survey methods often leads to significant estimation errors due to subjective bias and data limitations. To mitigate these issues, this research employed a systematic mapping approach rather than relying on direct parameter estimation. More specifically, the analytical process involved exhaustively examining all

plausible combinations of the relevant investor parameters. This comprehensive mapping allowed the study to account for a broad range of possible investor profiles and market scenarios, thus enhancing the completeness of the results.

The following parameter values were defined for the mapping procedure:

Table 3.1: Parameter ranges used for the mapping procedure.

Parameter	Values
Time Horizons (H_m)	1, 5, 10, 20 years
Omega (Ω)	0.05, 0.1
Eta (η)	0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9, 1
Delta (δ)	0.01, 0.02, 0.03, 0.04, 0.05

3.3 Rationale Behind Parameter Selection

The parameters and their respective ranges were carefully chosen to reflect a realistic and inclusive spectrum of investor behaviours and risk attitudes. First of all, regarding the time horizons chosen, they are designed to span the entire investment lifecycle; in particular, these 4 time frames chose let us cover for short term investors (who are targeting liquidity), mid-term investors (whose plans can be represented by home purchases or educational expenses) and, finally, long-term investors (who's focus tends to be on retirement).

Secondly, the parameter eta, following prospect theory introduced by Kahneman and Tversky (1979), it counts for the asymmetry in risk perception. In order to include in the analysis the whole spectrum of investors' preferences, we can state that the range $\eta = \{0, 0.1, \dots, 1\}$ is broad enough to encompass a wide variety of psychological preferences, from highly risk-averse to moderately risk-tolerant investors.

Furthermore, the deviation from the expected return (δ), captures the investor's tolerance for deviation from the expected return, representing concern over the precision of performance outcomes. Lower values of δ indicate stricter performance requirements, while higher values reflect a willingness to accept some deviation. The chosen values ($\delta = 0.05, 0.1, 0.2$) offer sufficient variation to represent different degrees of flexibility regarding return expectations.

And finally Omega, the threshold tolerance, two values were selected: $\Omega = 0.05$ and 0.1, corresponding to 5% and 10% maximum tolerance, respectively. These thresholds are commonly used in risk management to represent conservative and moderately conservative investor behaviours.

By analysing the entire parameter space through this mapping strategy, the methodology ensures that the diversity of investor behaviours and preferences is fully considered. This provides a robust foundation for evaluating the model's outcomes across realistic and varied scenarios.

Section 4

Results and Discussion

4.1 Findings

It is now time to go along and present the results and findings of this work. This chapter presents a detailed breakdown of the performance and statistical characteristics of the structured investment products under analysis. Each section provides a discussion of the key empirical results for each single product, focusing on the behaviour of expected returns, risk measures, and distributional properties such as skewness and kurtosis across various investment horizons. The chapter, then, will include also a comparative discussion, synthesizing the main findings and highlighting the distinctive features and relative advantages of each strategy, highlighting which products are best for different kind of investors. Before going through the results for each product, it is thought insightful to take a look at the distributions (see figure 4.1) of the expected returns for each of the product in analysis. This is in fact important to understand in particular the choices of the product for different types of investors.

4.1.1 Protective Put Strategy

The first product analysed is the protective put strategy, in which the one-month Treasury Bill is almost always selected as the underlying asset, except when $H_m = 20$ and the investor is risk neutral ($\eta = 1$), in which the most profitable underlying is the one with Gaussian low volatility features. This selection arises directly from the optimisation procedure, which evaluates a variety of potential underlying assets and consistently identifies the T-Bill as offering the highest expected returns for all the possible combinations of parameters, thus considering both short-term (one year) and long-term (twenty years) investment horizons.

Very interestingly, after studying the link between delta and the expected return via linear regression, results reveal a (statistically significant) positive linear relationship. This finding clearly indicates that with higher investors' tolerance corresponds higher expected return. Moreover, in all scenarios tested, the optimal allocation involves investing the entire portfolio in the protective put constructed on the T-Bill (thus the amount invested in options correspond with 100% of the underlying asset), with no deviation from this allocation across different investment horizons. This consistency highlights the robustness of the T-Bill as the preferred underlying asset under risk-neutral preferences.

From a distributional perspective, skewness analysis exhibits only modest variation:

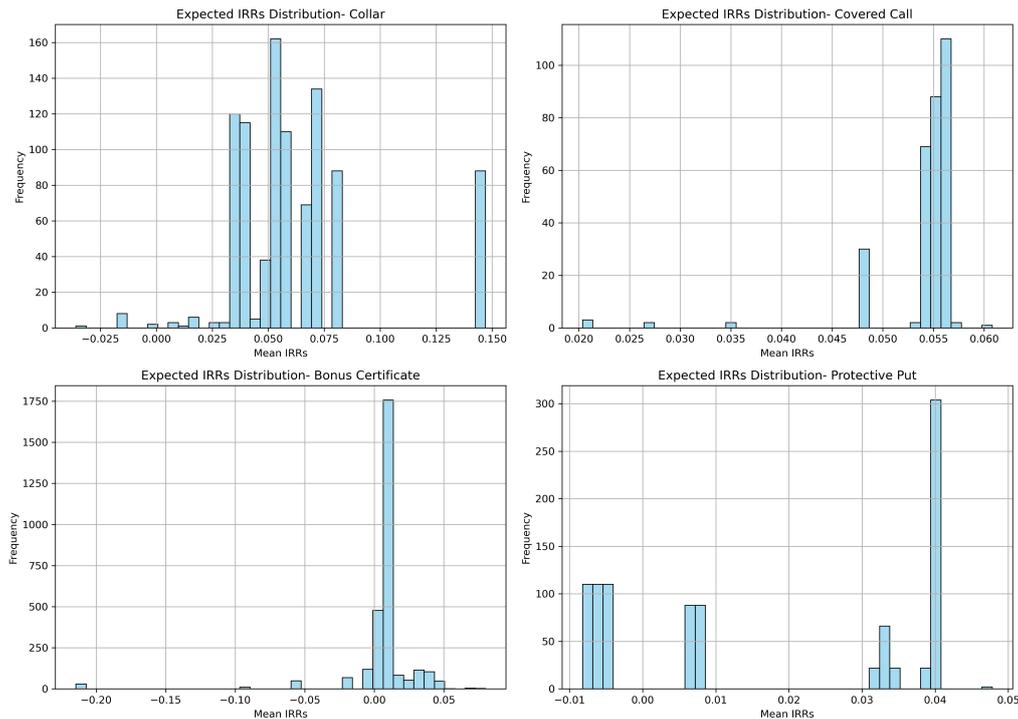


Figure 4.1: Distribution of IRRs for different structured products.

as the investment horizon extends from 1 to 10 years, average skewness decreases from 0.273 to approximately -0.003, remaining low at 0.0354 at 20 years. This persistence is attributed to the stable nature of the underlying asset, which results in minimal shifts in return distributions over time. Kurtosis also shows a slight downward trend as the horizon lengthens, ranging from 0.0286 to 0.037. Across all scenarios, the return distribution remains consistently platykurtic, underscoring the stable and predictable character of the protective put strategy when implemented using a T-Bill as the underlying asset. These outcomes further underscore the strategy's appeal as a conservative and robust investment choice.

4.1.2 Bonus Certificate

Now, turning to the bonus certificate product, the analysis reveals that the choice of underlying asset does not change across different omega (risk parameter) values, even when extending the investment horizon to 5, 10, or 20 years. Nevertheless, asset selection becomes more complex than the protective put case: in the short-term (one year), the optimal underlying may be either a T-Bill (when the investor is more risk averse) or a Gaussian/Nskewed asset (for risk-neutral or risk-seeking individuals). During the mid-term (five to ten years), T-Bills continue to dominate for low level of eta ($\eta = [0, 0.1]$), with low-volatility Gaussian assets appearing in the other cases. By the long-term (twenty years), assets with lottery-type payoff profiles are consistently selected, offering higher expected returns irrespective of risk tolerance. Unlike the protective put case, for the bonus certificate there is no statistically significant relationship between delta and the expected return. Portfolio allocation is also straightforward: almost all capital is devoted to the derivative (the auto-call) component, except for four isolated exceptions. The return distribution for bonus certificates exhibits higher average skewness

in the short term, suggesting a heavier right tail and the potential for higher returns, while longer-term investments see more symmetric distributions. Similarly, kurtosis is elevated for short- and mid-term horizons (one to ten years), signifying heavier tails, but shifts to platykurtic (light-tailed) behavior in the long term (twenty years). These results indicate that bonus certificates offer both higher upside potential and greater distributional risk for shorter holding periods but converge to stable and predictable outcomes over longer durations.

4.1.3 Covered Call

The covered call strategy is characterized by a largely stable underlying asset, with only three scenarios deviating from this pattern: investor will tend to choose 1-month Treasury Bill as underlying. For the short term, expected returns are lower (0.0481), accompanied by greater standard deviation (0.0105). In the mid-term, expected returns rise moderately (0.0543871 and 0.05544), while standard deviation falls (0.004726 and 0.0033463). The long-term scenario yields the highest expected returns (0.0559823) and the lowest standard deviation (0.0023621). Furthermore, the regression analysis indicates no statistically significant link between delta and expected return for covered calls (p-value = 0.13899). Interestingly, the derivative (call option) component is almost always zero, with the entire investment consisting in T-Bills or Gaussian stock. Skewness shows no systematic pattern due to the constancy of the underlying, fluctuating around zero (maximum 0.0696, minimum -0.132 for the Gaussian case). Kurtosis remains near zero for all horizons, with the distribution consistently platykurtic. Collectively, these results confirm that the covered call approach delivers stable, predictable return profiles with minimal extreme outcomes, largely independent of the investment horizon.

4.1.4 Collar Strategy

Similarly, the collar strategy does not show changes in the choice of underlying across different omega values, regardless of investment horizon. For short-term investments, the underlying can be either a T-Bill or a leptokurtic/n-skewed asset, reflecting risk aversion or neutrality, respectively. In the mid-term, the underlying shifts to lottery-type assets, while in the long term, an n-skewed asset is preferred for all risk profiles. Notably, the collar strategy displays a statistically significant and positive linear association between delta and expected return, confirmed by a regression's p-value of 0.000847. In terms of portfolio allocation, the entire derivative allocation is consistently assigned to the put option and is zero for the call, except in three short-term cases. As a result, the collar closely approximates the protective put in practical terms. Skewness reveals an interesting non-monotonic pattern: it is minimized at the shortest horizon ($T = 1$), maximized at $T = 5$, and then declines as the horizon extends to twenty years. Kurtosis follows the same trajectory, also minimized at $T = 1$, peaking at $T = 5$, and subsequently declining for longer horizons. Once again, the actual collar displays unique kurtosis dynamics compared to its components, underscoring the nuanced risk-return profiles inherent in collar constructions.

4.2 Comparative Analysis

A comparison of the four structured products reveals very interesting results that are worth to be stressed and highlighted. First of all, from an underlying type perspective, both the protective put and covered call strategies clearly favor the one-month Treasury Bill as the underlying asset, reflecting their conservative nature and emphasis on capital preservation. The collar strategy also demonstrates limited variation in asset choice, favoring T-Bills or stable assets for short horizons but transitioning toward lottery-type or n-skewed assets as the investment horizon extends. In contrast, the bonus certificate's optimal underlying asset evolves more dynamically with investor risk tolerance and investment horizon: T-Bills dominate for risk-averse investors in the short term, while Gaussian, n-skewed, or lottery-type assets become preferred as either risk tolerance increases or horizons lengthen, indicating a more opportunistic approach to capturing upside potential. Very interesting is also the relationship between delta and the expected return: a statistically significant and positive linear relationship emerges only for the protective put and collar strategies, suggesting that these products reward greater risk tolerance with higher expected returns. For the bonus certificate and covered call products, no such link is detected, implying that other factors govern their return dynamics and risk exposures.

Furthermore, in both the protective put and collar strategies, allocation is highly concentrated: for the protective put, the entire portfolio is invested in the T-Bill and the corresponding put, while for the collar, all derivative allocation is assigned to the put option (with the call allocation nearly always zero). This suggests a strong tilt toward downside protection in both strategies. The bonus certificate strategy also favors full allocation to the derivative component (the auto-call), reinforcing its risk-seeking profile, with only rare exceptions. For the covered call, the derivative component is almost always zero, so the investment is effectively held entirely in the underlying (typically a T-Bill). From a distribution perspective, all four products display generally platykurtic return distributions, especially over long investment horizons, highlighting a tendency toward light tails and limited exposure to extreme outcomes. The protective put and covered call exhibit minimal variation in skewness and kurtosis, reflecting their stable and predictable profiles. Bonus certificates, however, show elevated skewness and kurtosis in the short and mid-term—signifying potential for higher returns (and risks) in the near term—before converging to stable distributions in the long run. The collar strategy stands out for its non-monotonic skewness and kurtosis, which both peak at intermediate horizons and then decline, indicating more complex and nuanced risk-return dynamics.

Overall, the protective put and covered call emerge as the most conservative options, delivering highly stable and predictable outcomes with minimal extreme results, largely irrespective of risk tolerance or investment horizon. The bonus certificate and collar, on the other hand, offer greater upside potential and more varied risk profiles, particularly in the short-to-medium term. The collar, in particular, shares many features with the protective put but introduces additional flexibility—and complexity—in its distributional properties.

In the following page is presented a summarizing table (4.1). The table reports, for each value of η , the portfolio statistics, the selected underlying asset type, the optimal allocations to call and put options, the value of delta, and the type of structured product corresponding to each scenario.

Table 4.1: Portfolio statistics comparison.

Parameters fixed: $\Omega = 0.05, H_m = 1$ year											
eta	0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1
expected return	0.048	0.048	0.048	0.048	0.0785	0.048	0.048	0.0534	0.0738	0.0608	0.048
underlying type	1-month T-bill	1-month T-bill	1-month T-bill	1-month T-bill	Gaussian low vol	1-month T-bill	1-month T-bill	Lepto high vol	Gaussian low vol	Gaussian low vol	1-month T-bill
std_irrs	0.0105	0.0105	0.0105	0.0105	0.0997	0.0105	0.0105	0.0708	0.0965	0.1438	0.0105
skew_irrs	0.0331	0.0331	0.0331	0.0331	0.6686	0.0331	0.0331	2.1035	0.7538	-0.1321	0.0331
kurt_irrs	0.0208	0.0208	0.0208	0.0208	1.3096	0.0208	0.0208	6.4587	1.7737	0.2712	0.0208
optimal_q_call	0	0	0	0	0	0	0	0	0	-	0
optimal_q_put	1	1	1	1	1	1	1	0.9995	0.9614	0.4475	1
delta	0.01	0.01	0.01	0.01	0.05	0.01	0.01	0.05	0.05	0.05	0.01
product	Collar	Collar	Collar	Collar	Bonus Certificate	Collar	Collar	Collar	Bonus Certificate	Covered Call	Collar

Note: Table 4.1 reports the statistics (expected return, standard deviation, skewness, kurtosis, underlying type and product) of the "best product" for time horizon of 1 year, $\Omega = 0.05$ and all levels of η .

Section 5

Conclusions and Limitations

As we have seen throughout this work, the HAMA model has been confirmed as very useful tool for evaluating structured products from a goal-based, behaviourally informed perspective. By integrating investor-specific factors, such as investment horizon, gain-loss asymmetry, and tolerance for deviations from expected returns, the HAMA model is able to capture unique features and biases that are typical for "normal investors", giving the possibility to overcome the limitations of the MPT framework highlighted in the previous chapters.

Empirical results indicate that each structured product exhibits a distinctive performance profile. Protective puts and covered calls are characterised as conservative strategies, delivering stable and predictable returns suited for risk-averse investors. In contrast, bonus certificates and collars provide enhanced upside potential and more complex risk-return dynamics, particularly over shorter horizons. The findings highlight that behavioural factors significantly drive product selection, as investor preferences shape optimal allocations and asset choices.

Nevertheless, this study has several limitations that needs to be pointed out. The model is based on assumptions of constant volatility and risk-free rates, which may not capture real-market complexities. Furthermore, omitting transaction costs, taxes, and liquidity constraints results in a simplified investment environment and may overstate the feasibility of certain strategies. Estimating investor-specific behavioural parameters poses an additional challenge; while the study used a mapping approach to simulate diverse investor profiles, capturing actual investor preferences remains difficult. Finally, the analysis is restricted to four structured products, excluding other complex instruments that might yield further insights.

Future research should aim to address these limitations by incorporating historical market data to validate the simulations and by exploring dynamic portfolio rebalancing strategies. The use of machine learning techniques could improve behavioural parameter estimation and broaden the product universe to include a wider variety of structured and hybrid instruments. Additionally, integrating sustainability preferences (such as ESG factors) would further enhance the model's alignment with the evolving priorities of contemporary investors.

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Appendix A

Supplementary Tables

Within this annex there are presented all the optimization tables for each product and for all the combinations possible parameters taken in analysis. For each table there will be presented the portfolio that maximizes the returns for the combination and it will give all the information on the product (such as type of underlying asset, statistics, and quantity of the derivative component).

Table A.1: Portfolio statistics for $T = 1$, $\Omega = 0.05$ (Protective Put).

Parameters fixed: $\Omega = 0.05$, $T = 1$												
eta	0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1	
mean_irrs	0.04075	0.04075	0.04075	0.04075	0.04075	0.04075	0.04075	0.04075	0.04075	0.04075	0.04075	
underlying type	1-month T-bill											
std_irrs	0.01041	0.01041	0.01041	0.01041	0.01041	0.01041	0.01041	0.01041	0.01041	0.01041	0.01041	
skew_irrs	0.02732	0.02732	0.02732	0.02732	0.02732	0.02732	0.02732	0.02732	0.02732	0.02732	0.02732	
kurt_irrs	0.02856	0.02856	0.02856	0.02856	0.02856	0.02856	0.02856	0.02856	0.02856	0.02856	0.02856	
optimal_q_put	1	1	1	1	1	1	1	1	1	1	1	
delta	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	

Table A.2: Portfolio statistics for $T = 5$, $\Omega = 0.05$ (Protective Put).

Parameters fixed: $\Omega = 0.05$, $T = 5$												
eta	0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1	
mean_irrs	0.04077	0.04077	0.04077	0.04077	0.04077	0.04077	0.04077	0.04077	0.04077	0.04077	0.04077	
underlying type	1-month T-bill											
std_irrs	0.00466	0.00466	0.00466	0.00466	0.00466	0.00466	0.00466	0.00466	0.00466	0.00466	0.00466	
skew_irrs	-0.01693	-0.01693	-0.01693	-0.01693	-0.01693	-0.01693	-0.01693	-0.01693	-0.01693	-0.01693	-0.01693	
kurt_irrs	0.01411	0.01411	0.01411	0.01411	0.01411	0.01411	0.01411	0.01411	0.01411	0.01411	0.01411	
optimal_q_put	1	1	1	1	1	1	1	1	1	1	1	
delta	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	

Table A.3: Portfolio statistics for $T = 10$, $\Omega = 0.05$ (Protective Put).

Parameters fixed: $\Omega = 0.05$, $T = 10$												
eta	0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1	
mean_irrs	0.04076	0.04076	0.04076	0.04076	0.04076	0.04076	0.04076	0.04076	0.04076	0.04076	0.04076	
underlying type	1-month T-bill											
std_irrs	0.00329	0.00329	0.00329	0.00329	0.00329	0.00329	0.00329	0.00329	0.00329	0.00329	0.00329	
skew_irrs	-0.00280	-0.00280	-0.00280	-0.00280	-0.00280	-0.00280	-0.00280	-0.00280	-0.00280	-0.00280	-0.00280	
kurt_irrs	-0.00808	-0.00808	-0.00808	-0.00808	-0.00808	-0.00808	-0.00808	-0.00808	-0.00808	-0.00808	-0.00808	
optimal_q_put	1	1	1	1	1	1	1	1	1	1	1	
delta	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	

Table A.11: Portfolio statistics for $T = 10$, $\Omega = 0.05$ (Covered Call)..

Parameters fixed: $\Omega = 0.05, T = 10$											
eta	0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1
mean_irrs	0.05544	0.05544	0.05544	0.05544	0.05544	0.05544	0.05544	0.05544	0.05544	0.05544	0.05544
underlying type	1-month T-bill										
std_irrs	0.00335	0.00335	0.00335	0.00335	0.00335	0.00335	0.00335	0.00335	0.00335	0.00335	0.00335
skew_irrs	0.0018	0.0018	0.0018	0.0018	0.0018	0.0018	0.0018	0.0018	0.0018	0.0018	0.0018
kurt_irrs	0.01734	0.01734	0.01734	0.01734	0.01734	0.01734	0.01734	0.01734	0.01734	0.01734	0.01734
optimal_q_call	1	1	1	1	1	1	1	1	1	1	1
delta	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02

Table A.12: Portfolio statistics for $T = 20$, $\Omega = 0.05$ (Covered Call).

Parameters fixed: $\Omega = 0.05, T = 20$											
eta	0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1
mean_irrs	0.05598	0.05598	0.05598	0.05598	0.05598	0.05598	0.05598	0.05598	0.05598	0.05598	0.05598
underlying type	1-month T-bill										
std_irrs	0.00236	0.00236	0.00236	0.00236	0.00236	0.00236	0.00236	0.00236	0.00236	0.00236	0.00236
skew_irrs	-0.00550	-0.00550	-0.00550	-0.00550	-0.00550	-0.00550	-0.00550	-0.00550	-0.00550	-0.00550	-0.00550
kurt_irrs	0.01461	0.01461	0.01461	0.01461	0.01461	0.01461	0.01461	0.01461	0.01461	0.01461	0.01461
optimal_q_call	1	1	1	1	1	1	1	1	1	1	1
delta	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02

Table A.13: Portfolio statistics for $T = 1$, $\Omega = 0.1$ (Covered Call).

Parameters fixed: $\Omega = 0.1, T = 1$											
eta	0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1
mean_irrs	0.04811	0.04811	0.04811	0.04811	0.04811	0.04811	0.04811	0.04811	0.04811	0.04811	0.04811
underlying type	1-month T-bill										
std_irrs	0.01049	0.01049	0.01049	0.01049	0.01049	0.01049	0.01049	0.01049	0.01049	0.01049	0.01049
skew_irrs	0.03354	0.03354	0.03354	0.03354	0.03354	0.03354	0.03354	0.03354	0.03354	0.03354	0.03354
kurt_irrs	-0.01475	-0.01475	-0.01475	-0.01475	-0.01475	-0.01475	-0.01475	-0.01475	-0.01475	-0.01475	-0.01475
optimal_q_call	1	1	1	1	1	1	1	1	1	1	1
delta	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02

Table A.14: Portfolio statistics for $T = 5$, $\Omega = 0.1$ (Covered Call).

Parameters fixed: $\Omega = 0.1, T = 5$											
eta	0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1
mean_irrs	0.05433	0.05433	0.05433	0.05433	0.05433	0.05433	0.05433	0.05433	0.05433	0.05433	0.05667
underlying type	1-month T-bill	Gaussian low vol									
std_irrs	0.00473	0.00473	0.00473	0.00473	0.00473	0.00473	0.00473	0.00473	0.00473	0.00473	0.06957
skew_irrs	-0.01508	-0.01508	-0.01508	-0.01508	-0.01508	-0.01508	-0.01508	-0.01508	-0.01508	-0.01508	-0.06859
kurt_irrs	0.01704	0.01704	0.01704	0.01704	0.01704	0.01704	0.01704	0.01704	0.01704	0.01704	0.62218
optimal_q_call	1	1	1	1	1	1	1	1	1	1	1
delta	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02

Table A.15: Portfolio statistics for $T = 10$, $\Omega = 0.1$ (Covered Call).

Parameters fixed: $\Omega = 0.1, T = 10$											
eta	0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1
mean_irrs	0.05544	0.05544	0.05544	0.05544	0.05544	0.05544	0.05544	0.05544	0.05544	0.05544	0.05544
underlying type	1-month T-bill										
std_irrs	0.00335	0.00335	0.00335	0.00335	0.00335	0.00335	0.00335	0.00335	0.00335	0.00335	0.00335
skew_irrs	0.0018	0.0018	0.0018	0.0018	0.0018	0.0018	0.0018	0.0018	0.0018	0.0018	0.0018
kurt_irrs	0.01734	0.01734	0.01734	0.01734	0.01734	0.01734	0.01734	0.01734	0.01734	0.01734	0.01734
optimal_q_call	1	1	1	1	1	1	1	1	1	1	1
delta	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02

Table A.16: Portfolio statistics for $T = 20$, $\Omega = 0.1$ (Covered Call).

Parameters fixed: $\Omega = 0.1, T = 20$											
eta	0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1
mean_irrs	0.05598	0.05598	0.05598	0.05598	0.05598	0.05598	0.05598	0.05598	0.05598	0.05598	0.05598
underlying type	1-month T-bill										
std_irrs	0.00236	0.00236	0.00236	0.00236	0.00236	0.00236	0.00236	0.00236	0.00236	0.00236	0.00236
skew_irrs	-0.00550	-0.00550	-0.00550	-0.00550	-0.00550	-0.00550	-0.00550	-0.00550	-0.00550	-0.00550	-0.00550
kurt_irrs	0.01461	0.01461	0.01461	0.01461	0.01461	0.01461	0.01461	0.01461	0.01461	0.01461	0.01461
optimal_q_call	1	1	1	1	1	1	1	1	1	1	1
delta	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02

Table A.17: Portfolio statistics for $T = 1$, $\Omega = 0.05$ (Bonus Certificate).

Parameters fixed: $\Omega = 0.05, T = 1$											
eta	0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1
expected return	0.03060	0.03060	0.03060	0.05874	0.06584	0.06584	0.06584	0.06584	0.06584	0.04682	0.04682
underlying type	1-month T-bill	1-month T-bill	1-month T-bill	Gaussian low vol	NSkew 1	NSkew 1	NSkew 1	Gaussian low vol	NSkew 1	NSkew 1	NSkew 1
std_irrs	0.00354	0.00354	0.00354	0.06354	0.06551	0.06551	0.06551	0.06354	0.06551	0.06354	0.06354
skew_irrs	52.54188	52.54188	52.54188	1.03565	1.65437	1.65437	1.65437	1.03565	1.65437	1.03565	1.03565
kurt_irrs	5422.11082	5422.11082	5422.11082	3.36955	1.65437	1.65437	1.65437	3.36955	1.65437	3.05165024	3.05165024
optimal_q_call	1	1	1	1	1	1	1	1	1	1	1
delta	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05

Table A.18: Portfolio statistics for $T = 5$, $\Omega = 0.05$ (Bonus Certificate).

Parameters fixed: $\Omega = 0.05, T = 5$											
eta	0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1
expected return	0.00635	0.00635	0.01714	0.01714	0.01714	0.01714	0.01714	0.01714	0.01714	0.01714	0.01714
underlying type	1-month T-bill	1-month T-bill	Gaussian low vol								
std_irrs	0.00204	0.00204	0.00204	0.00204	0.00204	0.00204	0.00204	0.00204	0.00204	0.00204	0.00204
skew_irrs	20.65310	20.65310	1.77264	1.77264	1.77264	1.77264	1.77264	1.77264	1.77264	1.77264	1.77264
kurt_irrs	3166.58935	3166.58935	3.58633	3.58633	3.58633	3.58633	3.58633	3.58633	3.58633	3.58633	3.58633
optimal_q_call	1	1	1	1	1	1	1	1	1	1	1
delta	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05

Table A.19: Portfolio statistics for $T = 10$, $\Omega = 0.05$ (Bonus Certificate).

Parameters fixed: $\Omega = 0.05, T = 10$											
eta	0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1
expected return	0.00316	0.00316	0.00316	0.00316	0.00316	0.00316	0.00316	0.00316	0.00316	0.00316	0.00316
underlying type	1-month T-bill										
std_irrs	0.00172	0.00172	0.00172	0.00172	0.00172	0.00172	0.00172	0.00172	0.00172	0.00172	0.00172
skew_irrs	8.48903	8.48903	8.48903	8.48903	8.48903	8.48903	8.48903	8.48903	8.48903	8.48903	8.48903
kurt_irrs	1483.84803	1483.84803	1483.84803	1483.84803	1483.84803	1483.84803	1483.84803	1483.84803	1483.84803	1483.84803	1483.84803
optimal_q_call	1	1	1	1	1	1	1	1	1	1	1
delta	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05

Table A.20: Portfolio statistics for $T = 20$, $\Omega = 0.05$ (Bonus Certificate).

Parameters fixed: $\Omega = 0.05, T = 20$											
eta	0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1
expected return	0.01032	0.01032	0.01032	0.01032	0.01032	0.01032	0.01032	0.01032	0.01032	0.01032	0.01032
underlying type	Lottery-type 2										
std_irrs	0.00520	0.00520	0.00520	0.00520	0.00520	0.00520	0.00520	0.00520	0.00520	0.00520	0.00520
skew_irrs	-0.11967	-0.11967	-0.11967	-0.11967	-0.11967	-0.11967	-0.11967	-0.11967	-0.11967	-0.11967	-0.11967
kurt_irrs	-1.65053	-1.65053	-1.65053	-1.65053	-1.65053	-1.65053	-1.65053	-1.65053	-1.65053	-1.65053	-1.65053
optimal_q_call	1	1	1	1	1	1	1	1	1	1	1
delta	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05

Table A.21: Portfolio statistics for $T = 1$, $\Omega = 0.1$ (Bonus Certificate).

Parameters fixed: $\Omega = 0.1, T = 1$											
eta	0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1
expected return	0.03030	0.03030	0.03030	0.03030	0.04532	0.06584	0.06584	0.06584	0.06584	0.07339	0.07339
underlying type	1-month T-bill	1-month T-bill	1-month T-bill	1-month T-bill	Gaussian low vol	NSkew 1	NSkew 1	NSkew 1	NSkew 1	Gaussian low vol	NSkew 1
std_irrs	0.00381	0.00381	0.00381	0.00381	0.06392	0.06543	0.06543	0.06543	0.06392	0.07351	0.07351
skew_irrs	52.54188	52.54188	52.54188	52.54188	1.41664	1.65437	1.65437	1.65437	1.41664	1.65437	1.65437
kurt_irrs	5422.17062	5422.17062	5422.17062	5422.17062	1.41664	1.65437	1.65437	1.65437	2.74305	1.65437	1.65437
optimal_q_call	1	1	1	1	1	1	1	1	1	1	1
delta	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05

Table A.22: Portfolio statistics for $T = 5$, $\Omega = 0.1$ (Bonus Certificate).

Parameters fixed: $\Omega = 0.1, T = 5$											
eta	0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1
expected return	0.00635	0.00635	0.01714	0.01714	0.01714	0.01714	0.01714	0.01714	0.01714	0.01714	0.01714
underlying type	1-month T-bill	1-month T-bill	Gaussian low vol								
std_irrs	0.00230	0.00230	0.00205	0.00205	0.00205	0.00205	0.00205	0.00205	0.00205	0.00205	0.00205
skew_irrs	20.65310	20.65310	1.77264	1.77264	1.77264	1.77264	1.77264	1.77264	1.77264	1.77264	1.77264
kurt_irrs	427.55236	427.55236	3.58633	3.58633	3.58633	3.58633	3.58633	3.58633	3.58633	3.58633	3.58633
optimal_q_call	1	1	1	1	1	1	1	1	1	1	1
delta	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05

Table A.23: Portfolio statistics for $T = 10$, $\Omega = 0.1$ (Bonus Certificate).

Parameters fixed: $\Omega = 0.1, T = 10$											
eta	0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1
expected return	0.00316	0.00316	0.00316	0.01202	0.01202	0.01202	0.01202	0.01202	0.01202	0.01202	0.00316
underlying type	1-month T-bill	1-month T-bill	1-month T-bill	Gaussian low vol	1-month T-bill						
std_irrs	0.00172	0.00172	0.00172	0.00207	0.00207	0.00207	0.00207	0.00207	0.00207	0.00207	0.00172
skew_irrs	8.48903	8.48903	8.48903	2.38732	2.38732	2.38732	2.38732	2.38732	2.38732	2.38732	8.48903
kurt_irrs	1483.84803	1483.84803	1483.84803	3.87982	3.87982	3.87982	3.87982	3.87982	3.87982	3.87982	1483.84803
optimal_q_call	1	1	1	1	1	1	1	1	1	1	1
delta	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05

Table A.24: Portfolio statistics for $T = 20$, $\Omega = 0.1$ (Bonus Certificate).

Parameters fixed: $\Omega = 0.1, T = 20$											
eta	0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1
expected return	0.01032	0.01032	0.01032	0.01032	0.01032	0.01032	0.01032	0.01032	0.01032	0.01032	0.01032
underlying type	Lottery-type 2										
std_irrs	0.00700	0.00700	0.00700	0.00700	0.00700	0.00700	0.00700	0.00700	0.00700	0.00700	0.00700
skew_irrs	-0.11967	-0.11967	-0.11967	-0.11967	-0.11967	-0.11967	-0.11967	-0.11967	-0.11967	-0.11967	-0.11967
kurt_irrs	-1.65053	-1.65053	-1.65053	-1.65053	-1.65053	-1.65053	-1.65053	-1.65053	-1.65053	-1.65053	-1.65053
optimal_q_call	1	1	1	1	1	1	1	1	1	1	1
delta	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05

Table A.25: Portfolio statistics for $T = 1, \Omega = 0.05$ (Collar).

Parameters fixed: $\Omega = 0.05, T = 1$											
eta	0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1
expected return	0.04811	0.04811	0.04811	0.04811	0.04811	0.04811	0.05343	0.05337	0.04811	0.04811	0.04811
underlying type	1-month T-bill	NSkew 2	1-month T-bill	1-month T-bill	1-month T-bill	1-month T-bill					
std_irrs	0.01053	0.01053	0.01053	0.01053	0.01053	0.01053	0.07084	0.01783	0.01053	0.01053	0.01053
skew_irrs	0.02080	0.02080	0.02080	0.02080	0.02080	0.02080	0.56374	0.83686	0.02080	0.02080	0.02080
kurt_irrs	0.02080	0.02080	0.02080	0.02080	0.02080	0.02080	3.8516	6.83848999	0.02080	0.02080	0.02080
optimal_q_call	1	1	1	1	1	1	0.835978616	0.9394705	1	1	1
optimal_q_put	1	1	1	1	1	1	0.939504371	0.939943422	1	1	1
delta	0.01	0.01	0.01	0.01	0.01	0.01	0.05	0.05	0.01	0.01	0.01

Table A.26: Portfolio statistics for $T = 5, \Omega = 0.05$ (Collar).

Parameters fixed: $\Omega = 0.05, T = 5$											
eta	0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1
expected return	0.05442	0.05442	0.05442	0.05442	0.05442	0.06532	0.05442	0.05442	0.05442	0.05442	0.05442
underlying type	1-month T-bill	leptok high vol	1-month T-bill								
std_irrs	0.00471	0.00471	0.00471	0.00471	0.00471	0.07815	0.00471	0.00471	0.00471	0.00471	0.00471
skew_irrs	0.03617	0.03617	0.03617	0.03617	0.03617	2.34560	0.03617	0.03617	0.03617	0.03617	0.03617
kurt_irrs	0.0957	0.0957	0.0957	0.0957	0.0957	7.27416	0.0957	0.0957	0.0957	0.0957	0.0957
optimal_q_call	1	1	1	1	1	0.555171589	1	1	1	1	1
optimal_q_put	1	1	1	1	1	0.399504371	1	1	1	1	1
delta	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01

Table A.27: Portfolio statistics for $T = 10, \Omega = 0.05$ (Collar).

Parameters fixed: $\Omega = 0.05, T = 10$											
eta	0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1
expected return	0.08019	0.08019	0.08019	0.08019	0.08019	0.08019	0.08019	0.08019	0.08019	0.08019	0.08019
underlying type	Lottery-type 1										
std_irrs	0.06826	0.06826	0.06826	0.06826	0.06826	0.06826	0.06826	0.06826	0.06826	0.06826	0.06826
skew_irrs	5.52326	5.52326	5.52326	5.52326	5.52326	5.52326	5.52326	5.52326	5.52326	5.52326	5.52326
kurt_irrs	56.62456	56.62456	56.62456	56.62456	56.62456	56.62456	56.62456	56.62456	56.62456	56.62456	56.62456
optimal_q_call	1	1	1	1	1	1	1	1	1	1	1
optimal_q_put	1	1	1	1	1	1	1	1	1	1	1
delta	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02

Table A.28: Portfolio statistics for $T = 20, \Omega = 0.05$ (Collar).

Parameters fixed: $\Omega = 0.05, T = 20$											
eta	0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1
expected return	0.06950	0.06950	0.06950	0.06950	0.06950	0.06950	0.06950	0.06950	0.06950	0.06950	0.07169
underlying type	NSkew 2	Gaussian low vol	1-month T-bill								
std_irrs	0.06237	0.06237	0.06237	0.06237	0.06237	0.06237	0.06237	0.06237	0.06237	0.03888	0.01703
skew_irrs	1.07449	1.07449	1.07449	1.07449	1.07449	1.07449	1.07449	1.07449	1.07449	0.39603	0.35698
kurt_irrs	3.05698	3.05698	3.05698	3.05698	3.05698	3.05698	3.05698	3.05698	3.05698	0.39603	0.11440
optimal_q_call	1	1	1	1	1	1	1	1	1	1	1
optimal_q_put	1	1	1	1	1	1	1	1	1	1	1
delta	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02

Table A.29: Portfolio statistics for $T = 1, \Omega = 0.1$ (Collar).

Parameters fixed: $\Omega = 0.1, T = 1$											
eta	0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1
expected return	0.04811	0.04811	0.04811	0.04811	0.04811	0.04811	0.04811	0.04811	0.04811	0.04811	0.04811
underlying type	1-month T-bill										
std_irrs	0.01053	0.01053	0.01053	0.01053	0.01053	0.01053	0.01053	0.01053	0.01053	0.01053	0.01053
skew_irrs	0.02080	0.02080	0.02080	0.02080	0.02080	0.02080	0.02080	0.02080	0.02080	0.02080	0.02080
kurt_irrs	0.02080	0.02080	0.02080	0.02080	0.02080	0.02080	0.02080	0.02080	0.02080	0.02080	0.02080
optimal_q_call	1	1	1	1	1	1	1	1	1	1	1
optimal_q_put	1	1	1	1	1	1	1	1	1	1	1
delta	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01

Table A.30: Portfolio statistics for $T = 5, \Omega = 0.1$ (Collar).

Parameters fixed: $\Omega = 0.1, T = 5$											
eta	0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1
expected return	0.05442	0.05442	0.05442	0.05442	0.05442	0.05442	0.05442	0.05442	0.05442	0.05442	0.05442
underlying type	1-month T-bill										
std_irrs	0.00471	0.00471	0.00471	0.00471	0.00471	0.00471	0.00471	0.00471	0.00471	0.00471	0.00471
skew_irrs	0.03617	0.03617	0.03617	0.03617	0.03617	0.03617	0.03617	0.03617	0.03617	0.03617	0.03617
kurt_irrs	0.0957	0.0957	0.0957	0.0957	0.0957	0.0957	0.0957	0.0957	0.0957	0.0957	0.0957
optimal_q_call	1	1	1	1	1	1	1	1	1	1	1
optimal_q_put	1	1	1	1	1	1	1	1	1	1	1
delta	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01

Table A.31: Portfolio statistics for $T = 10$, $\Omega = 0.1$ (Collar).

Parameters fixed: $\Omega = 0.1, T = 10$											
eta	0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1
expected return	0.08019	0.08019	0.08019	0.08019	0.08019	0.08019	0.08019	0.08019	0.08019	0.08019	0.08019
underlying type	Lottery-type 1										
std_irrs	0.06826	0.06826	0.06826	0.06826	0.06826	0.06826	0.06826	0.06826	0.06826	0.06826	0.06826
skew_irrs	5.52326	5.52326	5.52326	5.52326	5.52326	5.52326	5.52326	5.52326	5.52326	5.52326	5.52326
kurt_irrs	56.62456	56.62456	56.62456	56.62456	56.62456	56.62456	56.62456	56.62456	56.62456	56.62456	56.62456
optimal_q_call	1	1	1	1	1	1	1	1	1	1	1
optimal_q_put	1	1	1	1	1	1	1	1	1	1	1
delta	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02

Table A.32: Portfolio statistics for $T = 20$, $\Omega = 0.1$ (Collar).

Parameters fixed: $\Omega = 0.1, T = 20$											
eta	0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1
expected return	0.06950	0.06950	0.06950	0.06950	0.06950	0.06950	0.06950	0.06950	0.06950	0.06950	0.07169
underlying type	NSkew 2	Gaussian low vol	1-month T-bill								
std_irrs	0.06237	0.06237	0.06237	0.06237	0.06237	0.06237	0.06237	0.06237	0.06237	0.03888	0.01703
skew_irrs	1.07449	1.07449	1.07449	1.07449	1.07449	1.07449	1.07449	1.07449	1.07449	0.39603	0.35698
kurt_irrs	3.05698	3.05698	3.05698	3.05698	3.05698	3.05698	3.05698	3.05698	3.05698	0.39603	0.11440
optimal_q_call	1	1	1	1	1	1	1	1	1	1	1
optimal_q_put	1	1	1	1	1	1	1	1	1	1	1
delta	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02