CHAPTER 5

Quant Models for Robo-Advisors

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Contents

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5.1 Introduction

One of the main advantages of robo-advisory is the ability to offer a large number of investors automated and thus cost-efficient asset management that can still be tailored to the client's needs to a certain extent. The easy scalability combined with high individuality (compared to the still-dominant standard solutions for retail customers) is one of the great strengths of robo-advisory solutions (Bankenverband 2017). To take full advantage of these benefits, all the components of a robo-advisory platform must work together as effectively as possible. This, in turn, places demands on investment strategies that can be used in this context. It makes sense to favor concepts that are both automated and rule based and which can be easily parameterized to reflect individual client requirements. This is the only way to derive full benefit from the scaling advantages offered by robotics (Lam 2016).

When comparing robo-advisors with independently managed security accounts or (conventional) professional investment advisors, the benefits typically mentioned include the following: *low costs*, *focus on risks*, *technology instead of emotions*, and *transparency*. All four points can be attributed to automation benefits: As in other industries, automation also leads to a reduction in costs, as labor now represents the largest cost item in many areas. Risks, in turn, can only be quantified and controlled by financial mathematical models and calculations. This process is inherently linked to the use of computers and thus predestined to be part of robo-advisory.

The consistent and systematic adherence to an investment approach is significantly facilitated by a purely rule-based and thus technically mappable approach. The typical errors in investor behavior can also be greatly mitigated by the systematic use of smart, stringent approaches. One of the frequently observed but avoidable investor mistakes is to exit from a long-term successful systematic approach "at an inopportune time". An investment strategy that is understood and "supported" in its decisions thus helps investors to stay "on board" even in difficult market phases and to avoid logging in losses. Experience has shown that this advantage of a strictly rule-based and transparent investment strategy is often underestimated. If the investor has understood the basic rules of the investment strategy, he will be able to understand the strategy's behavior (and is outcome) in different market phases and will therefore be able to stick with the strategy even in difficult times, which in turn is important for the success of the investment in the long term. All four of these advantages originate from a common source and can ultimately be traced back to a largely automated use of algorithm-based investment decisions. Since robo-advisory is based on highly automated software platforms, it would be downright wasteful not to take advantage of the resulting benefits at the heart of the investment strategy itself (Lam 2016). We will, therefore, next take a closer look at this aspect.

5.2 What Strategies Are Suitable for Robo-Advisory?

To capitalize on the benefits offered by the technology, investment strategies are required that integrate seamlessly with existing technology and have the same structural benefits. From this point of view, purely quantitative strategies form part of a robo-advisory as the entire process can then be designed “from a single source”. In principle, discretionary investment strategies can also be successfully used in asset management. Discretionary strategies, on the other hand, move between the following two poles, that is, hybrids are also possible:

Individual
Every portfolio manager makes investment decisions solely for “his” portfolios. This can mean that portfolio manager A increases the equity allocation at a given point in time, for example while his colleague B reduces it on the same day. From the company’s perspective, this approach offers a considerable advantage: the diversification resulting from this organizational structure reduces the likelihood that all portfolios will perform poorly at the same time and lead to overall client dissatisfaction with the risk of concentrated cash outflows. However, a certain herd mentality of the formally independent fund managers cannot be ruled out even with this form of organization, as it is well known that it feels more comfortable to wander with the masses than to wander alone. Only purely quantitative processes are immune to such emotional appraisal processes.

In-House Strategy
An investment committee sets guidelines for the currently supported investment allocation, right up to uniform model portfolios, which must be implemented by all in-house fund managers. Diverging performances

of individual portfolios from the same company are thus avoided, but so are the benefits of style diversification.

The short outline of the two approaches already shows that in the context of a robo-advisory, only the second variant would be considered, if at all: uniform model portfolios that serve to control individual securities accounts by mapping them one-to-one. Although such an approach can actually be implemented, it is considerably more expensive than a purely quantitative solution, since the investment process used for controlling would have to be set up in an entirely discretionary manner, with all the associated disadvantages on the cost side. The cost advantages resulting from a larger number of target portfolios per sample portfolio are already being used today in asset management for smaller portfolios. The last step toward automation is no longer being taken here. However, fund-linked asset management with a small number of discretionarily managed funds of funds, to which the client portfolios are then allocated based on risk appetite, are already consistent with the solution outlined above. When "porting" to a robo-advisor platform, only the front end to the client would change: the investment advisor who makes the selection on behalf of the client on the basis of a predefined list of criteria would be replaced by the robo-platform. A further disadvantage of the discretionary solution approach lies in the limited transparency: although the investment decisions of the investment committee can be published, a uniform approach across all times and personnel changes cannot realistically be guaranteed. This circumstance will sooner or later have a negative impact on portfolios with very long-term horizons, for example for retirement provision purposes, since the investor's reasons for deciding on a certain model portfolio may have become obsolete over the years due to changes in the discretionary process. The disadvantages of discretionary approaches in the context of robo-advisory are that the degrees of transparency, continuity, and cost-efficiency that can be achieved with quantitative approaches can never be fully achieved. Quantitative approaches with transparent rules show their strengths precisely here (Satchell 2003): once an algorithm has been set up, it only requires comparatively inexpensive maintenance at runtime, while the discretionary approach relies on the ongoing work of a (cost-intensive) investment committee. As quantitative rules consist of a fixed, always identical set of rules, they can be made transparent to the investor to an arbitrary degree. Only copy protection, which is not achievable by law, will set limits here in practice, but not the investment strategy per se. An investment strategy that, for example, is decidedly aimed at seeking the same risk contributions per asset class at all times will continue to do so even after 10 or 20 years, that is, the advantage in terms of continuity, in addition to the transparency advantage, results in a type of “accompanying advantage” over the discretionary approach. We will therefore deal with purely quantitative approaches and identify those particularly suitable for use as part of robo-advisory.

5.3 What Quantitative Approaches Does the Robo-Advisory Model Offer?

Robo-advisory services take advantage of automated processes—it is important to pursue this idea consistently right down to the investment strategy. However, not every rule-based approach is equally suitable for use in a fully automated implementation. There are many technical approaches that evaluate historical price patterns and draw conclusions about the current market situation. A simple example would be the use of moving averages to determine entry and exit times for any given market (Brock et al. 1992). Such approaches can be very successful in practice. However, they are not based on a strictly scientific basis, but on the use of a (mathematically formulated) heuristic. In order to do this, the so-called back tests are carried out, but their prognostic significance or temporal stability is often not given. Here, too, “post-optimization” must be carried out on an ongoing basis in the future, at the strategic level rather than at the portfolio level. These strategies thus come close to discretionary strategies, with all the advantages and disadvantages already mentioned above, especially in terms of transparency and continuity. In order to take full advantage of the aforementioned options that are available in robo-advisory, the strategies used must therefore also have a high degree of stability over time (Meucci 2009; Grinold and Kahn 2012). Risk models satisfy this requirement, while return forecasting models have to be revised regularly and they are also disadvantageous in terms of the required transparency.

For this reason, we want to focus primarily on quantitative approaches that make do with pure risk management and do not include return forecasts in the optimization process. What strategies fall into this category? First of all, these are all quasi-stationary strategies in which only a regular rebalancing (practical adjustment frequencies range from weekly to annual) is carried out according to a fixed rule. This fixed rule can be, for example, an equal weighting or a weighting based on market capitalization.

Such strategies have been devised to be highly transparent and easy to implement. The latter point, however, ensures that these strategies can also be easily “replicated”, and thus they will always be subject to increased price pressure. From the provider’s perspective, more sophisticated approaches should not only be aimed at benefiting the investor. Thanks to the automated platforms, however, such more sophisticated approaches can be implemented with comparatively little additional cost. Added value for the client can be achieved, for example, through the following objectives:

- Maximization of the diversification effect
- Equal distribution of risks to the investment instruments contained in the portfolio
- Risk minimization
- Adherence to lower value limits
- Specification of a risk preference by choosing a target investment period

5.3.1 Maximization of the Diversification Effect

The old stock market wisdom of not putting all your eggs in one basket is often cited, but too often not consistently followed. To be clear: Many baskets are also of little use if they are mounted on the same bike rack and the whole bike tips over. It will be difficult to achieve a noticeable stabilization of the portfolio through diversification effects with equities from a single sector. A necessary but not yet sufficient prerequisite for a well-diversified portfolio is, therefore, an investment universe that not only consists of highly correlated components, but also makes targeted use of those with low or even negative correlations. The more the components differ, the greater is the chance that even in times of crisis the portfolio can be effectively hedged through opposing developments. Such a well-diversified investment universe is, therefore, also a necessary prerequisite for the construction of risk-controlled portfolios on robo-advisor platforms. However, this is only half the battle. The main audience for robo-advisor platforms are private investors who are unlikely to have any experience with investment mathematics. This is where the robo-advisor platform can demonstrate its strengths, for example, by determining the mixing ratio of the components for the available part of the investment universe, where the diversification effect is greatest. This approach can be formulated mathematically and transformed into an optimization problem (Choueifaty and Coignard 2008). All you have to do is maximize the diversification ratio DR, which can be determined as follows:

$$\max_{w_i} DR = \max \frac{\sum_{i=1}^{N} w_i \cdot \sigma_i}{\sigma_p} \tag{5.1}$$

given the boundary conditions

$$\sum_{i=1}^{N} w_i = 1$$

and

$$w_i \geq 0 \quad \forall \quad i = 1, \ldots, N$$

with w_i as weight of asset i within the portfolio, σ_i as volatility of asset i, σ_p as portfolio volatility, and N as number of assets. Or, put in another way, the diversification ratio can be expressed as portfolio risk without diversification divided by portfolio risk with diversification. Hence, the weighted sum of asset risk divided by the total portfolio risk equals the maximum diversification ratio DR at its peak. In this type of portfolio optimization, the ratio of the weighted individual risks of the asset classes (excluding diversification) to the actual portfolio risk (i.e. including diversification) is maximized. This process in the two-asset case can be illustrated as displayed in Fig. 5.1. If the two axes are swapped and the diversification ratio is also plotted, then the point you are looking for in the graph can be read directly as the maximum (see Fig. 5.2). The advantage of a portfolio structured in this way is that it has the highest risk-adjusted diversification effect of all portfolios that can be built from the investment universe (Choueifaty et al. 2013). Elements from the investment universe that diversify well are highly rewarded, even if, in themselves, they might not have been considered when using other portfolio structuring techniques (such as variance minimization) due to their volatility, which may be somewhat higher.

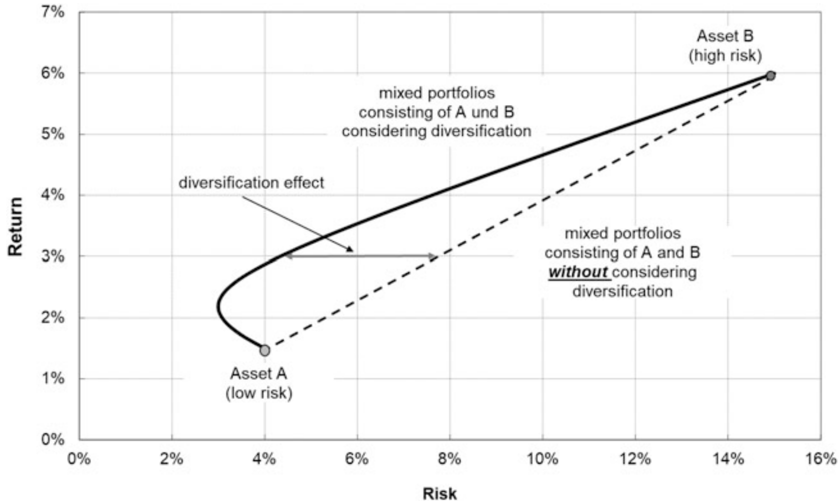

Fig. 5.1 Diversification effect

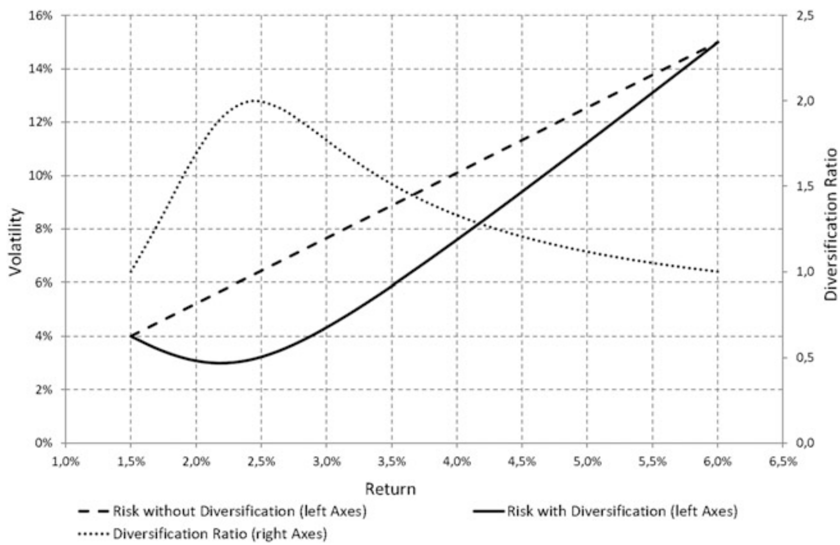

Fig. 5.2 Diversification ratio shows maximum at 2.0

5.3.2 *Equal Distribution of Risks to the Investment Instruments Contained in the Portfolio*

The maximum diversification approach described above not only optimizes the allocation weightings based on this target, but also implicitly selects the investment instruments from the investment universe, that is, not all available instruments are necessarily included in the portfolio. This can frustrate some investors who have actively chosen a number of instruments and are now disappointed not to find them all in their portfolio. In this case, there is a way to ensure that all previously selected instruments are actually included in the portfolio, while maintaining a balance between them in terms of risk. This method therefore assigns the same risk contribution to all instruments that are to be found in the portfolio. Portfolios built in this way have become quite popular in recent years and are referred to as "risk parity" portfolios. With risk parity, the portfolio is optimized in such a way that all instruments have the same contribution to the total risk (Teiletche et al. 2010).

$$PCTR_i = \frac{ACTR_i}{\sigma_p} = \frac{1}{N} \quad \forall \quad i = 1, ..., N \tag{5.2}$$

where N is number of assets, σ_p is portfolio volatility, $ACTR_i$ is absolute contribution to total risk of asset i, and $PCTR_i$ is percentage contribution to total risk of asset i. The advantage of a portfolio built in this way is that it avoids structural cluster risks. The correlations between the asset classes and thus their diversification potential are explicitly taken into account. However, during major financial market crises, the effect can be observed time and again that investors on a large scale close out risky positions across markets and regions and withdraw liquidity from the market. As a result, the correlations between these risky instruments rise abruptly during the crisis (so-called diversification breakdown). In other words, where there was protection by diversification at least on paper, when it is needed most urgently, it is gone.

In order to anticipate this effect of the increasing correlations in the crisis, a modified approach can therefore be chosen in advance, in which uniform volatility contributions are allocated instead of uniform risk contributions. This modification not only protects against unpleasant surprises during market corrections, but also offers the advantage of easier computation, as the portfolio weights can be calculated directly without having to carry out a (more time-consuming) optimization.

$$w_i \cdot \sigma_i \equiv w_j \cdot \sigma_j \quad \forall \quad i, j \Leftrightarrow w_i = \frac{\frac{1}{\sigma_i}}{\sum_{j=1}^{N} \frac{1}{\sigma_j}} \quad \forall \quad i = 1, , ..., N \tag{5.3}$$

with N as number of assets, w_i as weight of asset i, and σ_i as volatility of asset i. The latter modification retains the advantage of taking into account all preselected instruments from the investment universe. This also simplifies the calculation compared to the conventional risk parity method (as no optimization is required) and makes the portfolio less sensitive to a "diversification breakdown" at times of crisis.

5.3.3 Risk Minimization

The two purely quantitative approaches described above ensure that either the potential diversification effect is fully exploited for a given investment universe or that the risks contained in the portfolio are distributed as evenly as possible. For particularly risk-averse investors, however, it is advisable to make portfolios available that minimize the overall portfolio risk (Clarke et al. 2011):

$$\begin{aligned} \min_{w_i} \sigma_p^2 &= \min \sum_{i=1}^{N} \sum_{j=1}^{N} w_i \cdot w_j \cdot \sigma_{i,j} \\ &= \min_{w_i} \underbrace{\sum_{i=1}^{N} w_i^2 \cdot \sigma_i^2}_{\text{single risk part}} + \underbrace{\sum_{i=1}^{N} \sum_{\substack{j=1 \\ i \neq j}}^{N} w_i \cdot w_j \cdot \sigma_{i,j}}_{\text{diversification part}} \end{aligned} \tag{5.4}$$

with boundary conditions

$$\sum_{i=1}^{N} w_i = 1$$

and

$$w_i \geq 0 \quad \forall \quad i = 1, ..., N$$

as well as N as number of assets, σ_p^2 as portfolio variance, $\sigma_{i,j}$ as covariance of asset i and j, and w_i as weight of asset i.

Portfolios built in this way (generally based on factor models) have become popular in recent years due to their outperformance in equities. In theory, however, this portfolio has a serious disadvantage: it is "below" the capital market line, that is, the combination of a tangency portfolio and the risk-free investment leads (theoretically!) to the same low risk with higher expected returns. In practice, however, this disadvantage can be ignored: as return forecasts are needed to build a tangency portfolio. However, it is not possible to use historical data to come up with even short-term forecasts with the same confidence as it is the case with pure risk indicators. A tangency portfolio calculated using mean-variance optimization is, therefore, fraught with such uncertainty that the minimum variance portfolio, figuratively speaking, still lies within the error bars. The disadvantages that are relevant in practice are of a different kind: as with the portfolio with the maximum diversification ratio, even the minimum variance portfolio does not ensure that all previously selected instruments are included in the portfolio. In addition, the minimum variance optimization in mixed portfolios generally leads to a very high share of bonds, because it takes into account their low volatility, but not their low continuous yield.

5.3.4 Methods Based on Return Forecasts

The methods presented so far are purely risk based, that is, the expected return forecasts were deliberately omitted in order to circumvent the associated forecasting error issues. Even if forecast-free strategies have very advantageous characteristics despite the complete renunciation of an assessment of the market movement and have already been able to hold their own on the market (Clarke et al. 2013), it could, nevertheless, be argued that this in a way throws the baby out with the bathwater, because to avoid the problems associated with return forecasts, these have been completely foregone. In the following, therefore, we show a viable path to conventional portfolio optimization, in which a mean variance optimization (MVO), according to Markowitz, is performed using expected returns (Markowitz 1952):

$$U = \mu_p - \lambda \cdot \sigma_p^2 \tag{5.5}$$

where μ_p is expected portfolio return, σ_p^2 is portfolio variance, and λ is the risk aversion parameter.

The uncertainty under which the MVO is optimized takes into account only the dispersion of market returns, reflecting portfolio volatility σ. The return estimates for the individual portfolio components, which aggregate the expected portfolio return μ_p, are, however, implicitly assumed to be the exact mean of the distribution. This assumption, which is far removed from practice, leads to some very undesirable effects in portfolios optimized in this way: for example, in an MVO, highly correlated assets are considered perfect substitutes and are played "against each other" due to small differences in the return estimate, although the actual forecast error may be of the same magnitude as the estimated return spread. In other words, what at first glance looks like taking advantage of an arbitrage opportunity may turn out to be merely reinforcing a forecasting error ex post. Over time, comparatively small changes in the return estimates, which in reality, are due to forecasting errors, can lead to allocation leaps that ultimately rely on artifacts. These disadvantages of the MVO can be mitigated by a suitable transformation of return estimators. The Black-Litterman model (Litterman 2003) is, for example, very suitable for this purpose. The Black-Litterman model supplements the pure MVO with a process step in which the "raw" return estimators are modified as follows:

- Forecasts for highly correlated markets will be aligned based on this information. This counteracts the MVO's ability to treat highly correlated assets as perfect substitutes from a risk perspective and to "play them off" against each other in the event of diverging forecasts.
- Forecasts with higher confidence are given a greater consideration than those with lower confidence. This approach is intuitive. Borderline cases are pure MVO (all forecasts are highly reliable) and a preselected anchor portfolio (e.g. the investor's long-term benchmark portfolio) in the event that no reliable forecasts are available. In turn, the forecast-free approaches outlined above can be used as an anchor portfolio, so that in the event of high forecasting uncertainty an allocation that is advantageous from a pure risk perspective can be targeted.

The forecasting quality (confidence) can be determined by a sliding measurement of the variance of the forecasting errors, implicitly assuming a certain persistence in the quality of the estimates.

A fundamental disadvantage of forecast-based models, as mentioned at the beginning, is that return forecast models are associated with increased maintenance costs compared with pure risk models. However, this can be limited by picking the right model. Based on our own experience, the general regression neural network (GRNN), which is an extension of the probabilistic neural network (PNN) for non-discrete allocations, is very well suited, as it allows GRNNs to be used to approximate non-linear correlations such as price forecasts based on economically relevant variables. The GRNN is based on a very intuitive basic assumption: the more similar the past explanatory variables are to the current constellation, the more likely it is that the following price performance will closely resemble past performance. Another advantage of the GRNN is that only a single free parameter needs to be determined by optimization. This is the size of the neighborhood in the weighted approximation. If the chosen neighborhood parameter is infinitely large, on the one hand, an arithmetic averaging overall historical events will result. If the chosen neighborhood parameter, on the other hand, is infinitely small, the GRNN will simply act as a nearest neighbor estimator. Realistic neighborhood settings will of course lie between those two extremes.

The GRNN is ideally suited for adaptive forecasts, as each new input vector (consisting of the currently measured relevant economic variables) with the corresponding realized market return can be easily integrated into the existing database, and thus can be immediately fed into the next return estimate. This approach, therefore, has considerable advantages for robo-advisory services discussed here. With conventional regression analysis—if one wanted to use such an adaptive method—it would be necessary to reestimate the regression coefficients on an ongoing basis or to redevelop the regression function for every newly added data set completely from scratch, which would be even more time consuming. A detailed description of the procedure can be found, for example, in Specht (1991) and Rühl (2001).

5.4 Dealing with Risk Targets

5.4.1 Adherence to Lower Value Limits

The focus on and assessment of risks is rightly considered to be one of the benefits of robo-advisory services. The strategies presented above focus on the risk side: either by avoiding cluster risks, by maximizing the diversification effect, or by minimizing the overall risk. The possibility of automating a robo-advisor platform makes it possible to agree an individual lower value limit at the securities account level. Although lower value limits in the sense of capital preservation are no longer possible for a one-year time period due to the current interest rate environment, a previously accepted loss in value of max. 10%, for example, still represents a considerable limitation of the loss potential compared with an unsecured investment.

The maximum loss on the paid-up capital borne by the investor must be converted into an actual current maximum loss, which takes into account the previous market performance, that is, a positive market performance will increase the actual buffer available, while a negative market performance will erode part of the buffer. The buffer actually available on the basis of these two effects (initial buffer + market performance) then defines the maximum still acceptable value at risk (VaR_{max}) of the portfolio. If the actual value at risk (VaR_{act}) threatens to exceed the remaining buffer, the portfolio will have to become more defensive. The decision-making and control process that must be carried out continuously (and automatically!) in such a portfolio is as follows:

- As long as $VaR_{akt} \leq VaR_{max}$ applies, the current allocation can be retained or any safety measures can be resolved until $VaR_{akt} = VaR_{max}$ again.
- If, however, as a result of a negative performance or an increase in market risk with $VaR_{akt} > VaR_{max}$, a more defensive allocation must be selected until $VaR_{akt} \leq VaR_{max}$ again. The VaR reduction can be achieved either by adding liquidity or by choosing a more defensive but still fully invested allocation.

However, this procedure has one distinct disadvantage: the lower the available risk buffer, the higher is the probability that the portfolio will have to be completely removed from all risky investments (the so-called cash lock). Especially with long investment periods, it can happen that while the investment period, which is still available for value growth, can no longer be used, the portfolio remains "logged in" to the maximum loss. In other words, although it is technically feasible and even practicable at a reasonable cost to protect the value of an individual securities account, it raises the question of what to do in the case of a cash lock. In the case of conventional securities accounts, where clients have access to advisors, a solution can be found through dialogue. However, automated solutions must be offered as part of robo-advisory services. In the case of a hedging horizon of one year, a cash lock can, of course, be "paused" until a new risk buffer is made available again at the beginning of a new calendar year. If, however, a market reset occurs very early in the year that forces the portfolio completely out of the market and the market subsequently recovers, this usually leads to a high disappointment potential, as a negative portfolio result is offset by a positive annual financial statement at a market level. Other forms of risk management are available to avoid such potential conflicts going forward. For a practical implementation of risk targets, for example, an investment period to be chosen by the investor can be specified, at the end of which the invested capital is preserved with a sufficiently high degree of confidence. This takes advantage of the fact that the risk increase will be sharper than linear in the shorter term, but weaker in the long term (Danielsson and Zigrand 2006).

5.4.2 *Specification of a Risk Preference by Choosing a Target Investment Period*

Instead of working with a maximum loss target, investors can alternatively choose an investment horizon after which the invested capital is highly likely to be maintained at least nominally with a specified level of confidence (e.g. 95% or 99%). Over this period, the expected return of the portfolio "applies" and the expected value after this period is well above 0%. This type of risk target means that the investor is not confronted with very technical specifications such as the choice of a risk aversion parameter λ or a target volatility σ and can focus on the essential: a savings target in the future. Compared to a lower value limit for shorter periods, the advantage of this approach is that it is immune to the cash lock risk.

The mathematical-technical implementation of this specification takes place where it can be solved with comparatively little (additional) cost due to the existing infrastructure: on the robo-advisor platform. Even if short-term return forecasts are extremely unreliable, estimates of excess returns at the asset class level can be made, at least in the long term, with sufficient confidence for the purpose intended here. In order to calculate the required investment horizon for a certain allocation, one takes advantage of the effect that the risk of an investment will increase with the square root of time, that is, $\sigma \sim \sqrt{t}$, and it is thus stronger than linear in the short term, but weaker in the long term.

If one makes a conservative assumption (neglecting the compound interest effect) of a linear increase in the expected return over time, you can determine the point of intersection for each selected allocation and thus the investment period from which you can expect a capital preservation. This can be done for any confidence level using the z-factor of choice. If the investment strategies that can be mapped using the robo-advisory platform are categorized based on their risk/return profiles, it is possible to filter out from this strategy universe those that achieve the sufficiently high confidence point before or at the end of the desired investment horizon. Alternatively or additionally, in the case of mean-variance-optimized strategies, those risk aversion parameters which satisfy this condition can be determined.

5.5 Return Targets and Risk-Bearing Capacity: Need for Information

In discussions with investors, it repeatedly becomes clear that the full implications of the low interest rate environment for the return expectations of all asset classes are all too often insufficiently understood. As a result, there are often unrealistically high expected returns on the one hand and an inappropriate risk bearing capacity on the other. This dual distortion of expectations results in a high potential for disappointment. Anyone who pursues a 5% return target and believes they can do so risk-free in today's capital market environment will almost inevitably be disappointed. It is therefore necessary to provide information about the fundamental relationship between risk and return, which extends beyond regulatory requirements. This also includes fundamental cause–effect relationships. This basic understanding then helps in the selection of the investment strategies or their risk characteristics that are suitable for one's own investment needs.

Because risk premiums are paid relative to risk-free interest, this means that if risk premiums remain the same, total return expectations must decrease as the risk-free rate falls across all premium sources. This can only be compensated by an increased risk premium. According to our own experience, this is, however, not the case in the current environment. The low interest rate environment, therefore, not only affects money market-related forms of investment, but also lowers the realistic expected returns across all asset classes. Unfortunately, this is only one side of the coin. Due to the lower expected value, the return distribution as a whole shifts "to the left", that is, further into the negative range so that all percentiles in the negative range are more likely to occur. In other words: while the expected returns must be adjusted downward, the risk ratios have to be adjusted upward. These two factors should not be lost on new robo-advisor clients, who have made their last investment decision "some time ago".

Actively managed investment strategies may, under favorable circumstances, generate up to one percentage point of additional return for each percentage point of volatility, as a premium to withstand fluctuations. In the following, we will assess a strategy with an expected return of 2.5% p.a. and volatility of 3.0%. Even under this optimistic premise, the risk-bearing capacity required to maintain a confidence level of 99% for a return target of 2.5% p.a. is just under −4.5% on a one-year view. If a 95% confidence is sufficient, the risk-bearing capacity drops to −2.4%, but it is statistically exceeded every 20 years. For example, in the case of a ten-year government bond, the period during which the risk falls to zero means that after ten years, the bond is fully repaid. In the case of actively managed asset management with open maturities, no such risk-free time in the future can be identified, but as outlined above, one can statistically calculate the time after which the paid-in capital is retained or available again with a given confidence. This is done by taking advantage of the risk growing weaker over time (with normally distributed returns proportional to a root function of time) and then determining the time when the expected return will most likely exceed the risk. In order to retain the invested capital with a high probability and a return target of 2.5%, the investment horizon must be extended well beyond one year. In the above example, if the probability of loss over the course of a year is still around 20%, it will fall to just under 12% after two years and to around 3% after five years. After 7.8 years, the loss probability will only be 1%. However, government bonds with this residual maturity have a "guaranteed" negative yield. Figure 5.3 shows the relationship between confidence levels (90%, 95%, and 99%) and minimum

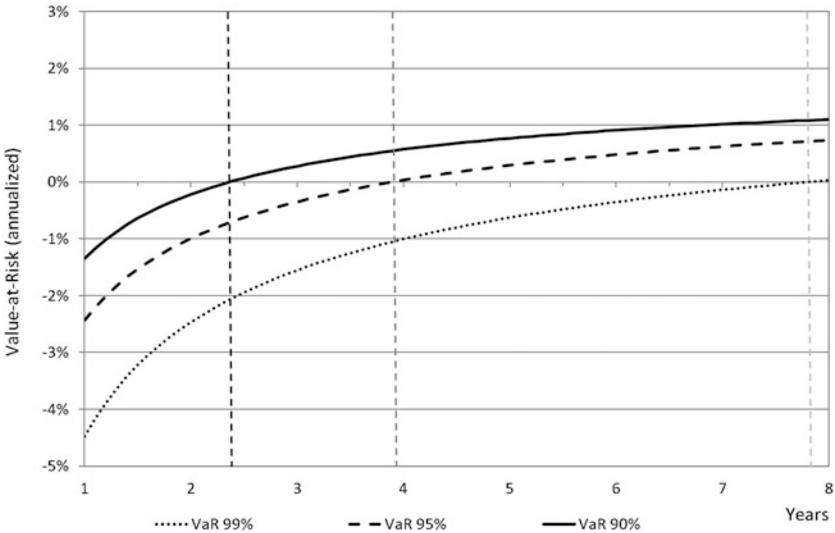

Fig. 5.3 Risk profile of a portfolio with 3% volatility and 2.5% expected return

investment duration for a defensive investment strategy (assumption: 3.0% volatility and 2.5% expected return): The solid line intersects with zero already after 2.4 years, that is, after this time the value at risk has dropped to 0 at 90% confidence level. It will take the aforementioned 7.8 years for the dotted line (99% confidence level) to intersect with 0.

To present these relationships to the (potential) investor at an early stage will also be worthwhile in the long term from the provider's point of view. While this may "put off" a few prospective clients in the short term, in the long term it will ensure a stable client relationship, as this was not entered into under the premise of unrealistically optimistic assumptions.

5.6 Requirements for the Investment Universe and Instruments

The requirements for the investment universe inevitably arise from the points already discussed. The investment universe must allow for sufficient diversification so that strategies focused on risk management can leverage their strengths. In addition, preference should be given to markets that can be modeled with sufficient precision using the risk models used on the platform. For volatility-based risk models, this means that market returns need to be approximated as normally distributed, which can be assumed in many liquid markets if the data frequency is not too high. Our own calculations have shown, for example, that in the current environment corporate bonds can be described with sufficient accuracy using a parametric value-at-risk, up to a confidence level of about 97%. However, in the case of higher confidence levels, the risk is increasingly underestimated when assuming normally distributed returns. In the case of a volatility-adequate mixture of equities and government bonds, the risk can be adequately estimated at the same data frequency with a confidence level of 99% with a (normal distribution-based) parametric value-at-risk.

In principle, it is possible to use simple (plain vanilla) components as part of a robo-advisory, which are then "refined" by using the relevant investment strategy. Although this means abandoning alpha at the component level. However, this potential disadvantage is offset by the fact that passive components are not exposed to the dangers of a manager change and can thus be modeled with a greater degree of confidence. In order to avoid inducing any further avoidable transactions such as rolling transactions other than those induced by the investment strategy, exchange-traded funds (ETFs) are preferable to derivatives despite slight cost disadvantages.

5.7 Customization by Investors

Robo-advisory requires a certain prior understanding on the part of the investor, but can use similar questions as conventional asset managers to lead the investor to the best possible solution. The investor should be able to select the following features of the portfolio or investment strategy:

- *Investment universe*: From the portfolio of available markets, the investor must be able to choose the markets or ETFs to be included (or excluded). To facilitate the selection process for less experienced investors, it is appropriate to define standardized solutions, for example German, Eurozone, European or world equities (or bonds).

If different strategy concepts are offered, this also applies analogously at the strategy level. As a general rule: If forecast-based strategies are used, they will generally operate on a narrower investment universe than the so-called forecast-free strategies. For this reason, the entire robo-platform investment universe will not be available for every investment strategy. To avoid overwhelming inexperienced investors, reasonable standard solutions should also be offered here that reflect the risk categories "conservative" to "aggressive". This can either take the form of several portfolios graded by risk (conservative, balanced, aggressive) or two basic portfolios at the extreme ends of the risk spectrum (conservative and aggressive), which are then combined to match the investor's chosen risk profile. This takes us to the next point.

- *The risk appetite* (see also "Risk targets over investment horizons"): Very few investors are able to specify their risk aversion parameters λ for a Markowitz-based optimization. A large proportion of the target audience of a robo-advisory platform will find it difficult to name a concrete target volatility.

Matters are complicated by the following effect, which can be observed quite often: Depending on the current market environment, strategies are often preferred that significantly overburden the investor's actual risk-bearing capacity in times of crisis. If such a risky strategy is in the immediate vicinity of a new all-time high, its inherent risk is typically underestimated, as "everything has always worked out fine". If the historical drawdowns, which can be recognized from the graphically visualized time series, are then experienced in real time, they are perceived as much more threatening: What if things do not work out fine this time? Often the investment is then terminated in an untimely manner, and the resulting loss is realized.

It is, therefore, more effective if the investor either specifies the maximum loss amount or specifies the investment horizon according to which at least the capital employed is highly likely to be obtained (or recovered). With the help of these specifications, those strategies can then be presented for further selection along with their risk characteristics that meet these conditions with a high degree of confidence. Depending on the complexity of the platform and the level of professionalism of the investor, a single standardized solution can be offered at this point, which adheres to both conditions.

5.8 Summary

Robo-advisory thrives on automation and quant models enable a high degree of automation on the strategy side. While quant models can work well in more conventional environments (this will remain the preferred choice for institutional investors for the foreseeable future), robo-advisory and quantitative investment strategies represent a very good structural fit. The cost savings that robo-advisory offers compared to conventional asset management can largely be passed on to the investor. This can deliver added value, especially compared to the highly standardized solutions for small investors that are otherwise customary on the market. Within the now broad spectrum of quantitative strategies, however, a distinction must be made: time-stable, low-maintenance models are preferable, which implicitly amounts to a renunciation of return forecasts. Strategies from the field of postmodern portfolio theory are optimal in this respect, which focus specifically on risk budgeting and/or risk minimization.

The strength of the models described here lies, among other things, in the control of portfolio risks not previously achieved by less affluent investors, right up to the specification of maximum loss limits or the specification of an investment horizon, according to which it is highly probable that the invested capital will be available again at least nominally. The models can also be set up in such a way that they are customizable by the investor within the previously defined framework. The complexity at the level of the selection process must accommodate the investor's level of experience. Less experienced investors should therefore continue to have access to a manageable number of standardized solutions in the future. While such standardized solutions are still often the state of play for all investment groups, the approaches shown here can also appeal to more demanding investors.

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